Modeling and Real-Time Control of Urban Drainage Systems: A Review☆

L. García^a, J. Barreiro-Gomez^{a,b}, E. Escobar^a, D. Téllez^a, N. Quijano^a, C. Ocampo-Martinez^b

^{a}Departamento de Ingeniería Eléctrica y Electrónica, Universidad de los Andes, Carrera 1^A No 18A-10, Colombia
^{b}Automatic Control Department, Universitat Politècnica de Catalunya, Institut de Robòtica i Informàtica Industrial (CSIC-UPC), Llorens i Artigas, 4-6, 08028 Barcelona, Spain

Abstract

Urban drainage systems (UDS) may be considered large–scale systems given their large number of associated states and decision actions, making challenging their real–time control (RTC) design. Moreover, the complexity of the dynamics of the UDS makes necessary the development of strategies for the control design. This paper reviews and discusses several techniques and strategies commonly used for the control of UDS. Moreover, the models to describe, simulate, and control the transport of wastewater in UDS are also reviewed.

Keywords: Modeling, real-time control

1. Introduction

Drainage networks are hybrid complex large–scale systems composed by several processes including collection, transport, storage, wastewater and/or rainwater treatment, and final disposition of treated water. UDS involve most of these processes inside cities and urban areas. UDS have a considerable social, economic, and environmental impact, so a correct and efficient urban drainage management to prevent flooding and polluting discharges to the environment is extremely important [1].

Depending on how wastewater and rainwater are managed, UDS can be either combined or separated. Combined sewage systems (CSS) carry wastewater and stormwater in a inosingle pipe, whereas the separated sewage systems (SSS) transport wastewater and storm water through independent pipes. During a rainstorm, wastewater flows can overload the CSS, producing flow discharges out from the network known as combined sewer overflows (CSO). Furthermore, some overflows incorporate back to the system after some external stages, e.g., an overflow going to streets might get back to the system throughout a different point within the network. In contrast, all the overflows discharges released to the environment without return to the system are flows that cause pollution. Consequently, CSOs can become pollution in case they do not return to the network, whereas the pollution is irreversible, i.e., a CSO

might become into pollution but not the opposite. From now on, CSOs are clearly differentiated from the pollution concept, and these two factors are treated independently for control objectives.

Over the last decades, climate change and the constant growth of cities and urban areas have had a considerable impact on UDS. On the one hand, population in cities has grown much faster than the infrastructure of its drainage networks [2]. On the other hand, the population growth in cities has required an increase in the construction of buildings, roads, and other civil infrastructures. As a result, the soil in these areas has lost rainwater absorption capacity, making cities more vulnerable to flooding in the presence of heavy rain events [3, 4]. Additionally, weather phenomena such as global warming have increased the frequency, intensity, and duration of rain events in many areas [2, 5]. All these circumstances have caused considerable increments in both wastewater and rainwater within cities, thereby increasing the risk of CSO and flooding events. Then, the minimization of the risk of CSO becomes an objective of great importance. To attain this objective, three main alternatives might be considered. The most evident solution consists in enlarging the infrastructure of the sewer system (either by adding more channels, pipelines and storage tanks [6] or by expanding the capacity of the existing ones), in order to transport water and sewage away from cities in a faster way and avoiding flooding. However, this solution generally involves high costs and the implementation times may be also high, making this solution unfeasible in many cases.

Other alternatives are related to the well-known *stormwater source control approaches*, which are aimed to reduce and/or delay runoff volume (i.e., provide rainfall capture) by managing in a suitable way the local water balance (e.g., promoting infiltration and evaporation, or delaying

---

the runoff by means of green roofs). Source control options (e.g., pervious paving, pervious pecks, rainwater re-use) can be complemented by the proper management of green infrastructures (e.g., parkland, forests, wetlands, greenbelts, floodways) [7]. Notice that techniques based on stormwater source control options might be effective according to the time scale considered and the dimension of the whole system. Their implementation should be analyzed according to the particular methodology, which in turn determines the associated costs with respect to the achieved goals [8, 9]. The previous discussion leads to the latter alternative, which consists in the reduction of the number and magnitude of overflows in UDS through an efficient management of the sewer system using the already existing infrastructure, requiring none or minimal volumetric expansion of the system. Such objective can be achieved by applying intelligent control systems to handle the UDS [10, 11].

Control of UDS can be performed either off–line (static rules) or on–line (real–time varying control actions). Due to the dynamic nature and complexity of drainage systems, as well as the dynamic loading conditions under which UDS operate, off–line control may not be the most appropriate option to be considered. Therefore, a dynamic control based on real-time information is necessary, then real–time control (RTC) appears as a suitable alternative to operate and manage UDS [12, 13]. The application of RTC to UDS has been studied by several researchers over the last years. Studies have shown that RTC is a reliable and cost-effective solution that improves the performance of UDS and that helps UDS to achieve operational objectives in a better way [14, 15, 16].

This paper presents a literature review of the main modeling and RTC techniques applied to UDS. A review of the main modeling approaches adopted for UDS is shown, a classification criterion is proposed, and the software tools (oriented to control and simulation) are also presented.

The remainder of the paper is organized as follows. Section 2 describes the characteristics of RTC when it is applied to UDS, and introduces some of the most used RTC techniques for these systems. Subsections 3.1 and 3.2 deal with the principal modeling approaches used to describe, simulate, and control UDS. Subsection 3.3 presents some of the main software tools to simulate and control such hydraulic systems. Finally, a discussion based on the literature review, and concluding remarks are shown in Section 4.

2. Real-Time Control of Urban Drainage Systems

UDS can be controlled in real time if process variables of the system are monitored and continuously used to operate actuators [16]. RTC algorithms consist of sets of rules that determine the control actions, which are taken in response to the current states of the sewer network [17].

The first RTC prototype for UDS was implemented at the end of the 1960s in Minneapolis–St. Paul (United States) [13]. Thenceforth, an increasing number of RTC strategies have been designed, simulated, and implemented for UDS all over the world, especially in Europe and North America.

Historically, the main objective in the application of RTC to UDS has been the reduction of volume in tanks and/or the total CSO, without having to make a volumetric extension of the already existing system [13]. Other objectives commonly taken into account include prevention of urban flooding and minimization of operational costs. More recently, further control objectives regarding water quality and pollution loads have also been considered. RTC algorithms may pursue more than one of these objectives simultaneously by using *multi–objective* control strategies. Additionally, operational objectives may change depending on the states of the UDS. This can be the case in countries where there are seasons or with large variations of the weather, where dry and wet seasons have quite different conditions.

It has been shown that the application of RTC techniques is a solution that allows the reduction of CSO volumes, among other benefits that, at the end, improve the performance of UDS [16, 18]. The two main reasons of why RTC improves the operation of the existing UDS are [13]:

1. Most parts of the UDS are historically designed according to static rules. However, the whole system is operated under dynamic loading conditions.

2. Climate change makes necessary to adapt sewer systems, which have a life expectancy of tens of years, to new loading situations. Singular climatic phenomena and problems such as global warming increase the urgency on real–time automatic operation.

RTC implementation includes several aspects such as hydraulics, instrumentation, remote monitoring, process control, software development, mathematical modeling, organizational issues, and forecasting of rainfall and/or flows. Implementation of all these aspects may be quite expensive, depending on the nature of each system. For this reason, RTC potential and benefits in an UDS must be identified before any implementation to justify the corresponding investments.

There is not a single criterion to determine whether or not an RTC implementation is suitable for a given UDS. In addition, there are some challenges that the application of RTC should face. These challenges that are considered in the decision–making process are [17]:

1. On-line measurements are the foundation of the RTC system. Processes that are unable to include monitoring sensors may not be suitable for the implementation of RTC. It is also important to determine whether the RTC system will use existing and already installed instrumentation, or if mostly new instruments are needed. Also, how well the processes are established, and the funding for maintaining those instruments.

2. Size of the system (normally of large–scale nature), overall hydraulic conditions, and dynamics of the sewer network.

3. Topology of the UDS and the general flow pattern (*looped* flow with many interconnections or *dendritic* flow pattern without many interconnections).

4. On–line storage possibilities, including the location of the major storage spots in the network and system topology (centralized and/or distributed/decentralized).

5. Organizational issues, including in–house expertise and available resources for the hydraulic modeling, RTC development and implementation, and future maintenance/support of the RTC module.

6. Overall information technology maturity of the organization interested in implementing RTC, i.e., how stable the SCADA (Supervisory Control and Data Adquisition) system is.

7. Number, complexity, flexibility, and operational experience with the actuators (e.g., gates, valves).

Efforts have been made to establish basic standard aspects to be taken into account when considering RTC implementation. One example of this is the working group in RTC of the German Association for Water, Wastewater and Waste (DWA in German), which prepared a guideline document on how to plan the RTC systems for urban drainage catchments (DWA M180) [19]. Software tools have also been designed to help in this decision process, e.g., the planning tool named PASST (Planning Aid for Sewer System RTC) [19, 20]. Furthermore, the essential components of a RTC system such as sensors, automated gates, and some strategies are described in [21].

There are numerous and quite different types of RTC strategies, and there are also many ways to classify them. Five different ways to classify RTC algorithms found in the literature are presented next.

The literature distinguishes between RTC strategies that are model–based and those that are not [17]. Among the most used control strategies for UDS, there are control strategies based on the system model such as model predictive control (MPC) and the linear quadratic regulator (LQR). This type of algorithms require a mathematical model that suitably describes the dynamical behavior of the plant. On the other hand, some decision–making strategies do not require a model of the system, but a complete knowledge on the system behavior. In general, this knowledge is hard to obtain. Some examples of these strategies are fuzzy–logic control (FLC) and rule–based control (RBC).

Another way to classify RTC strategies is into control algorithms based on optimization versus algorithms that use automated rules (rule–based algorithms) [17]. Rule–based systems consider the possible scenarios that can occur during the operation of the system, and have rules to determine the appropriate control actions. These kind of systems are usually easy to understand by the operators [17]. In contrast, optimization–based algorithms usually demand more computational efforts and a mathematical

representation of the system dynamics, but they are less dependent on the expert knowledge about the system, and these algorithms can generate control actions that produce an optimal performance.

Regarding the complexity of an RTC system, distinctions of the *class* or *level* of control implemented in UDS can be made [14, 16, 17, 18, 19, 22, 23, 24]. If the actuators are not remotely operated from a central control room, then the system is operated at a local level. On the other hand, the system is operated in a global control level when sensors communicate their data to other places of the system. There are many different configurations and communication architectures for this kind of control.

One of the most commonly used configurations of global control is the centralized control, in which a central control room receives all the measurement data from local sensors and centrally operates the actuators in a coordinated way. Consequently, the local control scheme may represent a more suitable solution in cases where there are few actuators in the system, but if the system is more complex or if all actuators have to be operated jointly, then the global control level is required [16].

In large–scale and complex systems, it is common to have both global and local levels of control. In this case, there can be up to three control levels. Firstly, there is a management level that provides the operational objectives and the performance index for the control system. Then, the global control level takes this information into account to produce the set–points for the local controllers, which are placed at different parts of the system. At the global control level the information from the system is gathered, including measurements at different points of the drainage network and measurements of disturbances of the system such as rain events (if available). Finally, the local control level receives the set–points, and operates the actuators accordingly [11]. This hierarchical structure is discussed in Section 3.

Distinctions between reactive systems and predictive systems can also be made. Reactive systems react to current (and possibly past) external events. Differently, predictive systems have forecasting mechanisms and methodologies to estimate future events, and take them into account to choose a control action. The addition of forecasting mechanisms in control systems may improve their performance, but it would add complexity to the mechanisms, since additional calculations and computations are required [17]. In the case of UDS, forecasts of variables such as rainfalls may give important and useful information about the system, although it might be deteriorated with the length of the forecasting horizons. For these reasons, benefits over the simpler reactive system should be identified in order to justify the increase of complexity and the expense of implementing forecasting.

The type of controlled variables is also an important criterion to classify RTC algorithms. Regarding this, the literature distinguishes between three different types of RTC: volume–based RTC, pollution–based RTC (PBRTC),

and water quality–based RTC (WQBRTC) [13]. Most RTC for UDS developed projects have focused only on waste–water volumes (volume–based RTC). In the last decade, the other two approaches have been taken more into account. Both PBRTC and WQBRTC require knowledge of the dynamics, not only the sewer network, but also about the waste–water treatment plant (WWTP) and the water bodies where the sewage is released. This means that an integrated model of the whole sewerage system is needed [16, 25, 26].

According to the mentioned classifications, and depending on the selected type of RTC strategy, different components are required for control implementation in UDS. Table 1 shows some of the components needed for the implementation of different control schemes in sewer systems. A detailed description of the measurement and control components used for applying RTC to UDS can be found in [27]. Once the generality of RTC has been presented, then the most used RTC techniques are introduced.

Table 1: Components required for different control configurations [17].

CONTROL MODEL	Instrumentation	Programmable logic controller	SCADA/ communic.	Central SCADA server	Active operator	Central RTC server	Rainfall forecasting	On–line model
Local manual control	✓				✓			
Local automatic control	✓	✓						
Regional automatic control	✓	✓	✓	✓				
Supervisory remote control	✓	✓	✓		✓			
Global automatic rule–based	✓	✓	✓	✓		✓		
Global automatic optimization	✓	✓	✓	✓		✓	✓	✓

2.1. Heuristic Algorithms

The main characteristic of heuristic algorithms is that these techniques are purely based on experience (knowledge already acquired). This means that a dynamical model of the system is not required to design the controller. In addition, the heuristic nature of these algorithms causes that any computed solution cannot guarantee optimality. Heuristic algorithms are usually developed to have low complexity, and they are generally used for systems that are quite complex to model [28].

In the case of UDS, the design of RTC based on heuristic algorithms does not need a control-oriented model of the system. However, simulation-oriented models[1] of the UDS are desired in order to evaluate the performance of these controllers, before their real implementation. Additionally, once these controllers are designed, they can be tuned. Then, an adequate simulation-oriented model helps in the improvement of the control performance.

One of the most broadly RTC heuristic algorithms used in UDS over the last decades is the rule–based control [30]. A particular rule-based strategy, known as fuzzy-logic control, has gained popularity in the application to UDS. A brief description of both conventional rule-based control strategies, and fuzzy-logic control is presented next.

2.1.1. Rule-Based Control (RBC)

Conventional RBC is one of the simplest RTC strategies that have been used in UDS. RBC for real–time flow control has been widely used in several UDS over the last decades. Hydraulic conditions, in a sewer system or in a WWTP, are important for the control of the system and the control actions must consider them. Therefore, the mentioned conditions are taken into account in the control system by using a large number of rules. For example, the CSO of a tank can be adjusted as a function of the water level in the storage tank as in [30].

RBC strategies are generally established off–line. This means that the control rules are specified before the process starts and they are represented in a way that allows a quick selection of the control actions, depending on the current state of the system. Examples of this kind of representations include "if–then" rules (where the "if" part depends on the current state of the system known as antecedent; and the "then" part represents the corresponding control action known as consequent), scenarios, and decision matrices correspond to a list of all possible combinations of inputs and current state variables in the process, relating them to the appropriate control actions [31]. Even if the rules of

---

[1]According to the literature (see, e.g., [29], among others), system models might reproduce their behavior with a desired accuracy, which is related to the complexity and manipulability of such models. Therefore, simulation-oriented models are only used for simulation purposes. On the other hand, control-oriented models (COM) are established to design model-based control strategies. Given that they should be used several times for complex computations, these COMs should be simpler and less accurate than the simulation-oriented models.

the control strategy are previously defined (off–line) and do not change, control actions depend only on the current state of the UDS at each time. Therefore, RBC computes the control action quickly and it can be considered as RTC.

Despite being one of the simplest RTC algorithms to implement, understand, and operate, RBC has some disadvantages. First of all, there is not a conventional methodology to establish the control rules for RBC. Rules are usually set by using the available expert knowledge about characteristics of the system and its behavior, so both the quality and performance of the rules and the controller highly depend on this expertise. Moreover, the expertise about the system may be obtained from the dynamical behavior of a model, i.e., the development of rules can be made by using a model of the system. Additionally, for large and complex systems the strategy may demand a huge number of rules and scenarios.

Briefly, the design of these rules depends on how the system behaves. An example of a rule might be as follows: "If a tank is close to be filled up, then all the inflows of the tank should be decreased in order to avoid an overflow".

2.1.2. Fuzzy–Logic Control (FLC)

Instead of conventional RBC systems, it is possible to use control strategies based on fuzzy logic. Fuzzy–logic control (FLC) is a control technique derived from fuzzy set theory. In contrast with classical binary logic where the variables can only have two values ('0' or '1') where Boolean algebra is used, variables in fuzzy logic are allocated to so–called degrees of membership ranging between 0 and 1, where the Kleene and D'Morgan algebras can be used to formalize mathematically the fuzzy rules [32].

FLC combines simple rules of an expert system with a flexible specification of output parameters. Conventional controllers adjust the control sizes of the system based on a set of differential equations that represent a model of a dynamical system. In fuzzy controllers, the control values are obtained on the basis of fuzzy rules, which are similar to the model of human reasoning [33].

The way in which fuzzy controllers produce control actions can be summarized in three steps. In the first step, scalar inputs are transformed into memberships of fuzzy sets by *fuzzifying* functions. This information is then given to the inference engine. Finally, the membership values are transformed into required scalar output variables by a *defuzzification* step [30]. This process requires that the fuzzy functions are already defined, in order to establish the degrees of membership of the inputs. FLC has been studied for reduction of CSO in UDS, and also for the control of WWTP [34].

The controllers of conventional RBC and FLC are different in many ways. Even the use of an identical rule base for both systems leads to different inference values [30]. The RBC and FLC have been studied in several applications involving UDS. In [35], a rule–based fuzzy algorithm is used to reduce overflows and the volume of CSO in the UDS of Wilhelmshaven (Germany), achieving both control

objectives. In [36], rule–based and fuzzy principles are used in Taiwan for the control of pumping operations in Taipei City sewage system, achieving a more effective draining of rainwater in order to avoid flooding in the city. Other applications of heuristic RTC techniques in UDS include the use of fuzzy expert systems to establish rehabilitation priorities of UDS in Laval (Canada)[37], and the use of FLC in urban drainage tunnels with nonlinear dynamics and random interferences, obtaining positive results such as improvement of the drainage system efficiency, extension of the pump lifetime, and a reduction in energy consumption [38].

2.2. Optimization–Based Algorithms

Optimization–based control algorithms involve an optimization problem that represents the desired behavior of the system. Based on the optimization problem and the measure (or estimation) of the current system variables, these algorithms seek the optimal control action. In UDS, optimization–based algorithms deal with the problem of generating control strategies in order to minimize or maximize certain criteria, based on current and past readings of the telemetry system [10].

The criterion to be minimized or maximized is usually expressed mathematically as a scalar function $J(\mathbf{x})$ known as objective or cost function. As it was previously stated, there can exist many different control objectives when applying RTC to UDS. Some objectives are [39]:

- Minimization of flooding in streets.

- Minimization of the CSOs to the receiving environment.

- Maximization of the treated sewage in the system.

- Minimization of operation costs (pump stations and treatment plants).

- Minimization of the water pollution released to the environment.

Regardless of the control objective for a particular UDS, this should be expressed as a cost function to solve the optimization problem. It is possible for some algorithms to take into account two or more control objectives. This is known as multi–objective control, and it can be done in several ways. One of the most widely used multi–objective techniques is called scalarisation. This technique consists in converting the problem into a single–objective optimization problem with a scalar–valued objective function [11]. This is done by forming a new objective function that is a linearly weighted sum of several single–objective cost functions. Thus, if there are N single–objective cost functions $J_1(\mathbf{x}), \ldots, J_N(\mathbf{x})$, a scalar weight w_i, with $i = \{1, ..., N\}$, can be assigned to each function, obtaining the new objective function

$$J(\mathbf{x}) = \sum_{i=1}^{N} w_i J_i(\mathbf{x}), \qquad (1)$$

where $\mathbf{x} \in \mathbb{R}^{n_x}$ corresponds to the state vector of the UDS, where $\mathbb{R}$ denotes the set of real numbers. There are different ways of assigning the weights w_i depending on the priority that each control objective has in a specific system. Other multi–objective techniques focus on the Pareto–optimal solution concept. A Pareto–optimal solution has the characteristic that one objective cannot be improved without worsening a different one [25]. Generally, there is more than one solution in a problem that satisfies this condition, generating sets of solutions known as Pareto sets. Additionally, several techniques use evolutionary approaches as well for solving multi–objective optimization problems. Examples of techniques based on these two notions can be found in [11, 25, 40, 41].

Most research has focused on single–criteria optimization so far. For this reason, multi–criteria optimization is an ongoing field [32]. An extensive review of several multi–objective optimization methods can be found in [42]. Some of the main optimization–based RTC algorithms are described below.

2.2.1. Linear–Quadratic Regulator (LQR)

LQR is an optimal controller that produces a linear control action in order to minimize an objective function $J(\mathbf{x}(t), \mathbf{u}(t))$ associated to the state variables norm (states $x_i(t)$, $i = 1, ..., n_x$) and the energy (control outputs $u_j(t)$, $j = 1, ..., n_u$). In general, the objective function J has the form

$$J(\mathbf{x}(t), \mathbf{u}(t)) = \frac{1}{2} \int_0^\infty \left(\mathbf{x}(t)^\top \mathbf{Q} \mathbf{x}(t) + \mathbf{u}(t)^\top \mathbf{R} \mathbf{u}(t) \right) dt,$$

where $\mathbf{Q}$ and $\mathbf{R}$ are weighting matrices with suitable dimensions that determine if the systems state $\mathbf{x}$ or the control action $\mathbf{u}$ are more suitable to be penalized. In the case of UDS, states $\mathbf{x}$ can be associated to volumes of the tanks, and the control actions $\mathbf{u}$ are associated to the manipulated flows in the system. The objective function J and its parameters are established according to the control objectives of the process.

For the LQR design, it is necessary to have a continuous–time state–space representation of the system given by

$$\frac{d\mathbf{x}(t)}{dt} = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t),$$

where $\mathbf{x} \in \mathbb{R}^{n_x}$ is the vector of states of the system, $\mathbf{u} \in \mathbb{R}^{n_u}$ is the vector of control actions (inputs to the system), and $\mathbf{A}$ and $\mathbf{B}$ are coefficient matrices with suitable dimensions. In order to minimize the objective function, LQR controllers produce the linear control law given by $\mathbf{u}(t) = -\mathbf{K}\mathbf{x}(t)$, where $\mathbf{K}$ is a gain matrix that must be found by solving a quadratic, first–order, ordinary differential equation known as the Riccati's equation [43].

In [44], multi–variable LQR is applied to sewer network flow control in Bavaria, Germany. In this case, the control objectives are the minimization of overflows in the system by using all available storage space in an optimal way, and emptying the network as soon as possible. Results of the study show positive performance with respect to the uncontrolled case, presenting the LQR as a valid alternative for the control of UDS. LQR techniques have also been applied in the RTC of water delivery and irrigation channels, in order to improve their delivery service [45].

2.2.2. Evolutionary Strategies (EA)

EA use and mimic evolutionary principles to seek optimal solutions. This kind of algorithms belong to the global optimization procedures, which do not require the assumption on the continuity of the objective function since they do not require information about the gradient of the function, making EA suitable for solving a very wide range of optimization problems [25].

Unlike classical methods, EA use a *population* representing a set of possible solutions at each iteration instead of evaluating just one possible solution. Therefore, these algorithms do not reach a single optimal solution of the optimization problem, but a set of commonly sub–optimal solutions. The ability to find multiple sub–optimal solutions in one single run makes evolutionary algorithms to be a suitable option to solve multi–objective optimization problems [25].

Most research in multi–objective optimization has mainly focused in Pareto–based optimization, a technique that involves a high computational burden. EA constitute therefore an important alternative, which can be more computationally efficient. In addition, EA allow the consideration of both linear and non–linear constraints and the handling of complex optimization problems.

One of the EA that has been studied and applied in the context of UDS is fuzzy decision making (FDM). This is a fuzzy–logic–based strategy, a decision making tool that can be used for multi–criteria optimization. Decision making can be described as the selection of the best alternative from a given set of possible choices, and the decision making approach gives information about the problem and goals to the decision maker. Since decision making resembles the selection of the best available alternative, it can be described mathematically as an optimization problem [46]. Also, these solutions are heuristic since they do not use an analytic mathematical procedure.

FDM allows to transform a multi–objective optimization problem into a single–objective problem by merging all partial objectives in one substitute quality criteria [32]. This technique has been applied in multi–criteria optimization of non–linear and dynamic control systems, showing advantages such as transparent criteria weighting, low computational effort and optimal trade–off between performance criteria, among others [47]. Knowledge–based approaches have also been used to support decision–making algorithms that aim to achieve environmental objectives in UDS, such

as reduction of pollution in rivers due to the waste–water discharges [48].

Other EA applied to UDS include genetic algorithms. These algorithms mimic the natural genetic processes of evolution, deliberately keeping a range of proper solutions to avoid being drawn into local optimal solution [49]. Genetic algorithms are usually used for solving complex and/or nonlinear optimization problems, or when the objective function is unknown. Examples of the application of genetic algorithms to water quality management systems and control of UDS can be found in [41] and [50]. In [25], evolutionary strategies combined with non–dominating sorting and self–adapting algorithms are applied to the control of integrated UDS, achieving an improvement in the receiving river water quality and lower investment costs.

2.2.3. Model Predictive Control (MPC)

MPC is a model–based control strategy that uses a prediction of the system response to establish an appropriate control action [51, 52]. This strategy makes an explicit use of a mathematical model of the process to generate a sequence of future actions within a finite prediction horizon. These actions, known as the control law $\mathbf{u}(k)$, are computed to minimize a given cost function. Notice that this approach is commonly designed in discrete time, where $k \in \mathbb{Z}$, denoting $\mathbb{Z}$ the set of integer numbers.

At time instant $k \in \mathbb{Z}$, the algorithm looks for a sequence of future control actions $\mathbf{u}(k), \mathbf{u}(k+1), \ldots, \mathbf{u}(k+H_p)$ within a finite–time horizon H_p previously determined. This sequence is obtained by solving an optimization problem based on the system predicted outputs and the cost function to be minimized. In practice, the controller can only apply the first action $\mathbf{u}(k)$. At time instant $k+1$, the same procedure is repeated, moving the prediction horizon one step ahead in time.

An MPC controller is composed by four main elements: a mathematical (control–oriented) model of the system, a cost function that expresses the control objective to be achieved, a set of system constraints (of bounding and operational nature), and a finite–horizon open–loop optimization problem, which is solved at each time instant [51]. Figure 1 shows the basic scheme of an MPC controller in a closed–loop topology.

The basic formulation of a linear MPC controller considers dynamic systems described by the discrete–time state–space model

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k), \tag{2}$$
$$\mathbf{y}(k) = \mathbf{C}\mathbf{x}(k), \tag{3}$$

where $\mathbf{y} \in \mathbb{R}^{n_y}$ is a vector containing the system outputs and $\mathbf{C}$ is a system matrix of suitable dimensions. In the most general case, the cost function of the optimization problem associated to the MPC algorithm may be a quadratic function of the form

$$J(\mathbf{x}, \mathbf{u}) = \sum_{j=1}^{H_p} \|\hat{\mathbf{x}}(k+j|k)\|_{\mathbf{Q}}^2 + \sum_{j=0}^{H_p-1} \|\hat{\mathbf{u}}(k+j|k)\|_{\mathbf{R}}^2.$$

Here, $\hat{\mathbf{x}}(k+i|k)$ and $\hat{\mathbf{u}}(k+i|k)$ denote the prediction of the state $\mathbf{x}(k+i)$ and the input $\mathbf{u}(k+i)$, respectively, from knowing (or estimated) $\mathbf{x}(k)$. The notation $\|\mathbf{x}\|_{\mathbf{Q}}^2$ denotes the quadratic form $\mathbf{x}^\top \mathbf{Q} \mathbf{x}$. In this cost function, $\mathbf{Q}$ is a positive semi–definite matrix and $\mathbf{R}$ is a positive definite matrix with suitable dimensions.

Let $\tilde{\mathbf{u}}$ be a control sequence given by $\tilde{\mathbf{u}} = [\hat{\mathbf{u}}(k|k)^\top \; \hat{\mathbf{u}}(k+1|k)^\top \; \ldots \; \hat{\mathbf{u}}(k+H_p-1|k)^\top]^\top$. The objective of the MPC controller is to find the optimal sequence $\tilde{\mathbf{u}}^*$ that minimizes the cost function $J(\mathbf{x}, \mathbf{u})$, while satisfying the existing restrictions in the system.

When applying MPC to UDS, a different type of inputs for the system may be taken into account. These inputs, called disturbances, cannot be manipulated by the controller. Thereby, it is necessary to modify the system model. In order to include disturbances in the model, (2) can be rewritten as

$$\mathbf{x}(k+1) = \mathbf{A}\mathbf{x}(k) + \mathbf{B}\mathbf{u}(k) + \mathbf{B}_p \mathbf{d}(k), \tag{4}$$

where $\mathbf{d} \in \mathbb{R}^{n_d}$ is a vector containing the system disturbances, and $\mathbf{B}_p$ is a system matrix of suitable dimensions. Table 2 shows the physical meaning that the variables $\mathbf{x}$, $\mathbf{u}$, and $\mathbf{d}$ would have in an UDS, according to the model proposed in [53].

Table 2: UDS variables.

Type of variable	Variable	Description
System states	$\mathbf{x}$	Tank volumes
Control inputs	$\mathbf{u}$	Manipulated flow through pipes and sewers
Measured disturbances	$\mathbf{d}$	Rain flow

Constraints in this case are given by the volumetric capacity of tanks and pipes, and by flow restrictions in pipes and actuators. These variables have maximum and minimum values, which must not be overstepped in order to ensure a proper system behavior. Moreover, the type of sensors and actuators used in the system may add extra restrictions. Regarding the cost functions, there are several options depending on the control objective that each UDS may have. Cost functions do not necessarily have the quadratic form of (2.2.3). Additionally, these functions can have different mathematical forms, and can take multiple control objectives into account, as it has been noted before. In the case of a multi-objetive MPC, scalarisation can be applied, obtaining a new objective function of the form (1). Moreover, a prioritization of multi-objective cost functions using the lexicographic approach might be applied [54].

The features of MPC controllers have certain advantages for their application to UDS. Some of them include the ability to explicitly express constraints in the system, the possibility to anticipate the response of the system to future rain events, and the capacity to consider non–ideal elements in the system such as delays and disturbances [55]. Other
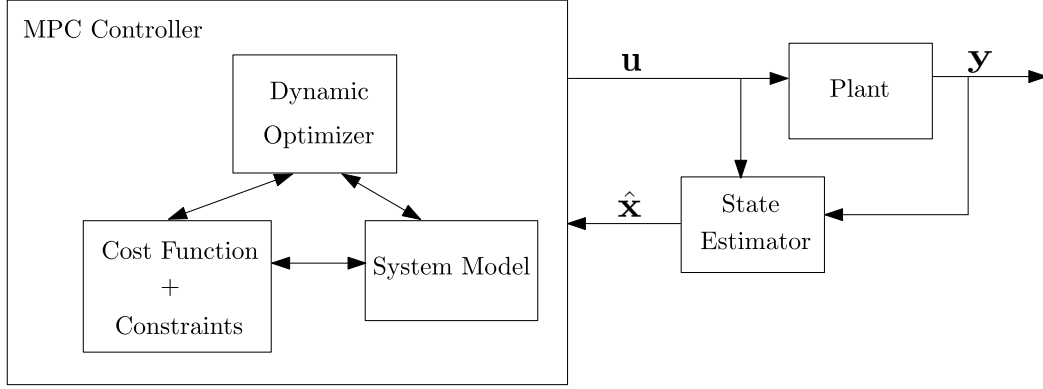
Figure 1: Closed–loop MPC configuration.

advantages of MPC include its suitability for multiple input multiple output (MIMO) systems, and for systems with complex dynamics.

Furthermore, MPC can be used to establish optimal references to local controllers. In this regard, MPC may use a control–oriented model of the system, whereas local controllers consider a more detail model to compute the final control action.

MPC strategies have been successfully applied in an increasing number of industrial applications during the last decades. In the case of UDS, MPC techniques have been applied and studied in several cities such as Barcelona, where an MPC controller is simulated in part of the city drainage network and it is shown that significant reductions in flooding and CSO may be achieved [10, 11, 53].

Predictive control has also been studied in Haute–Sure, Luxemburg. MPC techniques are being developed for a drainage system that gathers the sewage of 23 villages and several small settlements located around the Haute–Sure reservoir, and directs it to one main WWTP [22, 56]. Other countries where MPC has been studied and/or applied to UDS are: Canada [16], Germany [57], Colombia [58], and Netherlands [59].

MPC theory has been developed into a quite matured stage. However, some problems and subjects remain opened in this field, e.g., adaptive [60], and robust MPC [61, 62, 63]. Additionally, decentralized and distributed MPC configurations have become a growing research field. Distributed MPC has been studied for different applications including control and coordination of power systems [52, 64] and urban traffic control [65]. Decentralized and distributed MPC strategies have also been studied in water related applications such as level control in tanks [66] and coordination in water supply networks [67, 68, 69]. A review of different distributed MPC configurations and future research directions in this field can be found in [70].

Table 3 shows a comparison between the RTC techniques described in this paper. Aspects such as the ability to deal with constraints and non–linear dynamics in the system were taken into account for the comparison. The

configuration in which the control techniques can be implemented (centralized and/or distributed) was considered too, as well as their degree of implementation in applications related to UDS. Additionally, Table 4 shows a categorization of optimization-based and heuristic algorithms control strategies, as well as references of some cases where control strategies have been applied to UDS.

2.2.4. Population Dynamics-based Control (PD)

This control approach has already been studied for water systems [71]. The controller designed with this approach is inspired in a resource allocation problem, and its interpretation can be related to a biological evolution process. As in the fuzzy controller, this controller assigns dynamically the outflow from a tank throughout m possible paths wherever there is a control action available, and this decision making is made without requiring a system model. With this approach, the system states $\mathbf{x} \in \mathbb{R}^{n_x}$, introduced in previous sub-sections, are associated to the volumes of the tanks that compose the system denoted by $\mathbf{v} \in \mathbb{R}^{n_x}$. Moreover, we clarify that the m amount of considered tanks in this sub-section is a subset of the total number of tanks that compose the system (i.e., $m < n_x$).
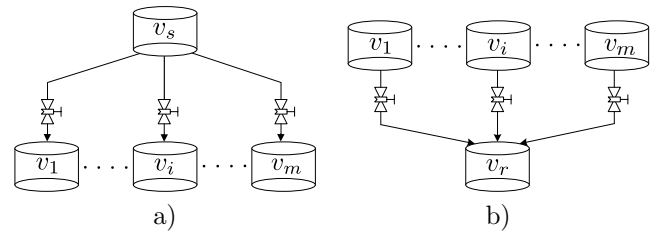

Figure 2: Resource allocation flow topology.

Consider a topology with one source tank T_s whose volume is denoted by $v_s(t) \in \mathbb{R}$, and m receptor tanks as shown in Figure 2a). Then, the outflow of the source tank T_s as a function of the current volume is given by $Q(v_s(t))$, and it should be optimally distributed throughout the receptor tanks by controlling the valves. Then, the flow

8

assigned to the receptor tank $v_i(t)$ is given by $Q(v_s(t))u_i(t)$, for all $i = \{1, ..., m\}$, where $u_i(t)$ establishes how opened the valve is. Moreover, notice that it should be satisfied that $\sum_{i=1}^n u_i(t) = 1$, since considering the sum of all the outflows from the source tank

$$\sum_{i=1}^m Q(v_s(t))u_i(t) = Q(v_s(t)) \sum_{i=1}^m u_i(t),$$
$$= Q(v_s(t)),$$

satisfying the distribution of the outflow throughout all the receptor tanks.

Now, consider a PD approach to allocate the resources. It is assumed that there is a population composed by a large number of agents that can select a strategy. The set of possible strategies is given by the receptor tanks, i.e., $\mathcal{S} = \{1, ..., m\}$. Let $u_i(t)$ be the percentage of agents selecting the strategy $i \in \mathcal{S}$, i.e., there is a proportion of the outflow going to the ith tank. For this approach, agents have incentives to select a certain receptor tank from the set of strategies $\mathcal{S}$. These mentioned incentives are given by a fitness denoted by $f_i(e_i(t))$ that is function of the error $e_i(t) = v_{maxi}(t) - v_i(t)$, where v_{maxi} denotes the capacity or maximum volume of the ith tank. In [72], these ideas have been used in order to control the case in which m different flows converge to one receptor tank T_r whose volume is denoted by $v_r(t) \in \mathbb{R}$. This topology is the one presented in Figure 2b).

In both topologies presented in Figure 2, the control actions are a probabilistic distribution between the m possible paths, then the vector of the percentage $\mathbf{u}(t) \in \mathbb{R}^m$ should belong to the invariant set denoted by

$$\Delta = \left\{ \mathbf{u}(t) \in \mathbb{R}^m : \sum_{i=1}^m u_i(t) = 1, u_i(t) \geq 0 \,\forall i \right\}.$$

Moreover, fitness functions $f_i(e_i(t))$ should be designed properly such that it has a decreasing trend with respect to the control action $u_i(t)$. For instance, in [71] fitnesses are shown as the error within each tank, i.e., there are more incentives to assign inflow to tanks with more error or available volumetric capacity. In contrast, in [72] fitness are shown as the volume at each tank, i.e., there are more incentives to assign outflow to tanks with more volume to avoid they achieve their maximum capacity.

The replicator equation introduced in [73], describes this dynamical process in which agents pursuit higher benefits, and it is given by

$$\frac{du_i(t)}{dt} = u_i(t) \left(f_i(e_i(t)) - \bar{f}(t) \right), \text{ for all } i \in \mathcal{S},$$

where

$$\bar{f}(t) = \sum_{i=1}^m u_i(t) f_i(e_i(t)).$$

The equilibrium point $u^*(t) \in \Delta$ for the replicator equation (5) implies that $f(e_i(t)) = f(e_j(t))$, for all $i, j \in \mathcal{S}$. In

both topologies, this strategy allows to take advantage of space in the network avoiding CSO. This model-free control approach represents an alternative solution for distributed and optimization-based controllers since this technique involves concepts from game theory.

3. Modeling Approaches

The urban water cycle is composed by different stages that include collection, transport, purification and conditioning for human needs, distribution, consumption, wastewater collection, depuration, and finally reuse or disposal in the natural environment. This paper focuses on the stage where the sewage produced by homes and businesses is collected and carried to treatment plants in order to avoid pollution to the environment.

UDS exhibit some specific characteristics that make them especially challenging to analyze and manage. These characteristics may include many complex features and/or behaviors as: large–scale architecture, nonlinear dynamics, hybrid dynamics, delays, disturbances, and operating constraints [11]. Mathematical models of UDS can be classified depending on how detailed they are, and also on how many stages they consider.

For instance, the *integrated models* include mainly information about WWTP and *receiving water body*. These models are used to predict possible future scenarios (e.g., impact of climate change, urbanization; see Figure 3). Within the integrated models, the following sub–categories can be found:

1. Models that include information of the cycle of the wastewater as rainfall–runoff, hydraulic transport, pollutant transport process, overflow–runoff, and WWTP [84, 85].

2. Models that include information about physical variables such as supply of water, climate, soil, air quality, and social variables such as economics, energy cost, demographic, ecological and urban models for decision–support systems in UDS [86].

3. Models that include process of transport and infiltration of urban wastewater in UDS, which can be modeled in an integrated form. They are described, with their pros and cons in [87, 88].

The use of a particular model among the different categories mentioned above can be discussed. For instance, in [85, 89] a comparison between simplified and detailed integrated urban modeling with respect to the water quality receiving on a water body is presented.

Due to the fact that the purpose of this survey is to present the most used models in the RTC design and its application, the previously mentioned integrated models are not the main models within the scope of this work. Since it is not necessary to include complete details of all the process stages of the UDS in order to design a controller, this paper focuses on models of water transport and particularly

Table 3: Features of RTC.

Type of Controller	Optimization Based	System Non–linearities	Consideration of Constraints	Centralized or Distributed	Model Free	Degree of Implementation
RBC – FLC	No	Yes	No	C / D	Yes	Medium
LQR	Yes	No	No	C	No	Medium
EA	Yes	Yes	Partially	C / D	Yes	Low
MPC	Yes	Yes	Yes	C / D	No	High
PD	Yes	Yes	Yes	C / D	Yes	Medium

Table 4: An overview of the control strategies for UDS.

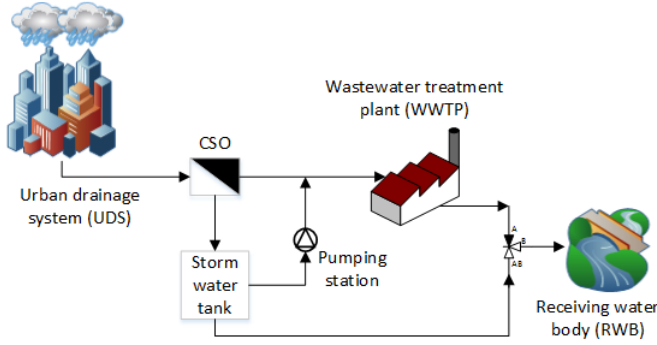| Control Strategies Applied to UDS						
Heuristic Algorithms		Optimization-based				
Fuzzy	Rule-Based	LQR	MPC		EA	Population Dynamics
[32] [34] [35] [36] [37] [38]	[30] [48]	[45] [49] [74]	[11] [51] [53] [54] [59] [67] [68] [69] [75] [76] [77] [78] [79] [80] [81] [82]		[25] [50] [83]	[71] [72]

Figure 3: Schematic representation of the integrated urban drainage system, adapted from [89].

on models of flow in open channel. Moreover, this paper proposes a classification of models into simulation–oriented models, and control–oriented models. The proposed classification of models is based on complexity and computational burden (see Figure 4).

Simulation–oriented models are known as *physically–based models*, where the equations that describe the propagation of a wave in an open channel are the *De Saint-Venant Equations* (SVE), which describe the conservation of mass and momentum [90].

In contrast, the control–oriented models have lower accuracy and complexity, and they are used for the design of controllers, leading to an accordingly limited design complexity and implying to moderate computational effort. These models can be grouped into three categories: simplified models, data–driven models, and conceptual models [23].

The main applications of the UDS models are for the

design of infrastructures [12, 91], and to design model-based controllers [92]. The features of each model should be evaluated for an appropriate selection of one of them. These characteristics are: the pursued objective, computational burden, and complexity of the model, which are briefly discussed next.

Regarding the models for design and simulation tasks, time is not a critical factor because these models do not need online computation, e.g., the curb of height, number and location of sewers, and the pipe of dimensions. On the other hand, for models aimed to RTC tasks, time is a critical variable because the model should be evaluated to obtain/compute a large number of control actions within a short selected sampling time. In general, higher performance and low uncertainty levels require higher model complexity [29].

Figure 5 shows: 1) the relationship for the operation of the UDS between the control space and real system, and 2) the relationship between the control space and simulation space for the design of the UDS. Finally, a discussion about the main models of UDS, categorized into simulation–oriented models and control–oriented models is presented in the next subsections.

3.1. Simulation–Oriented Models

Simulation–oriented models of UDS are mainly based on SVE. The SVE are two coupled nonlinear partial differential equations based on the physical principles of mass and energy conservation, which allow to describe accurately the flow in irrigation channels and sewers network [83, 93].

Due to the complexity to obtain an analytic solution of the complete SVE-based model in some cases it is convenient to make a simplification. Particularly, depending on the nature of the UDS, it may be possible to simplify the
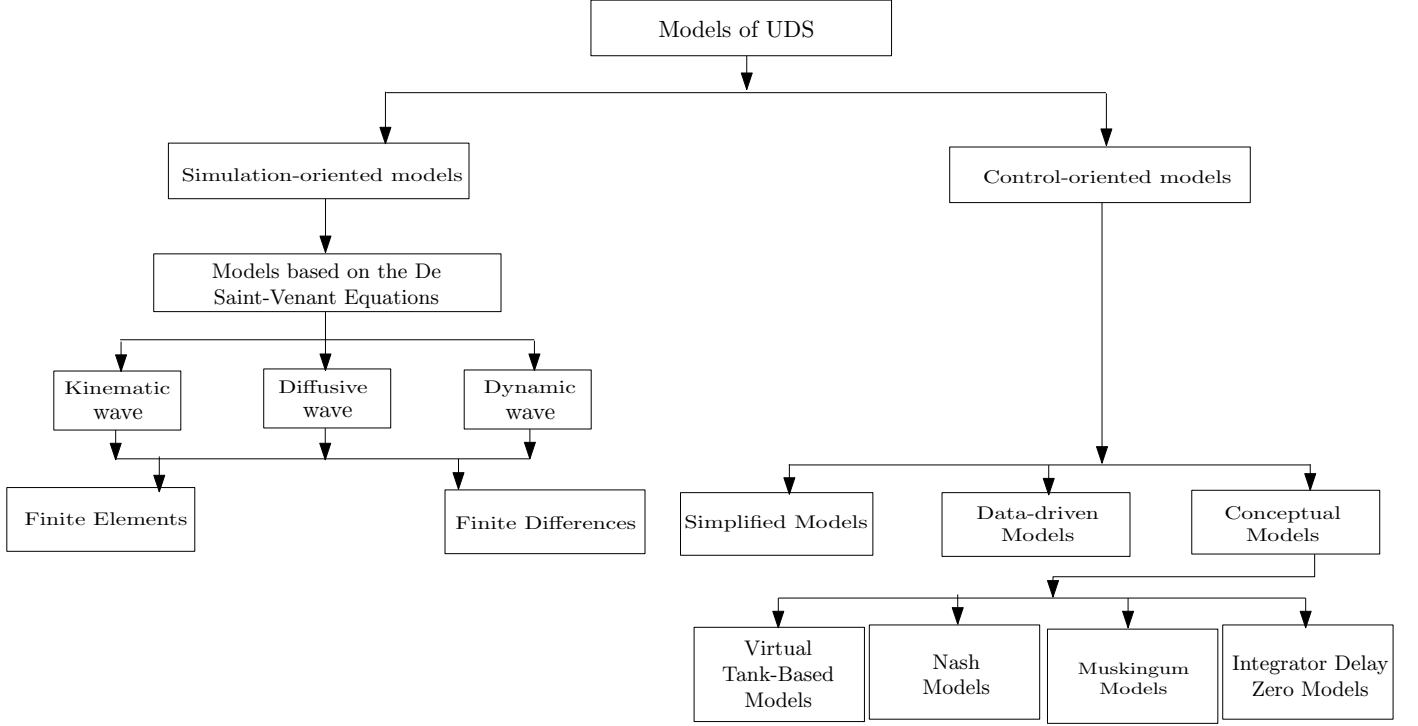
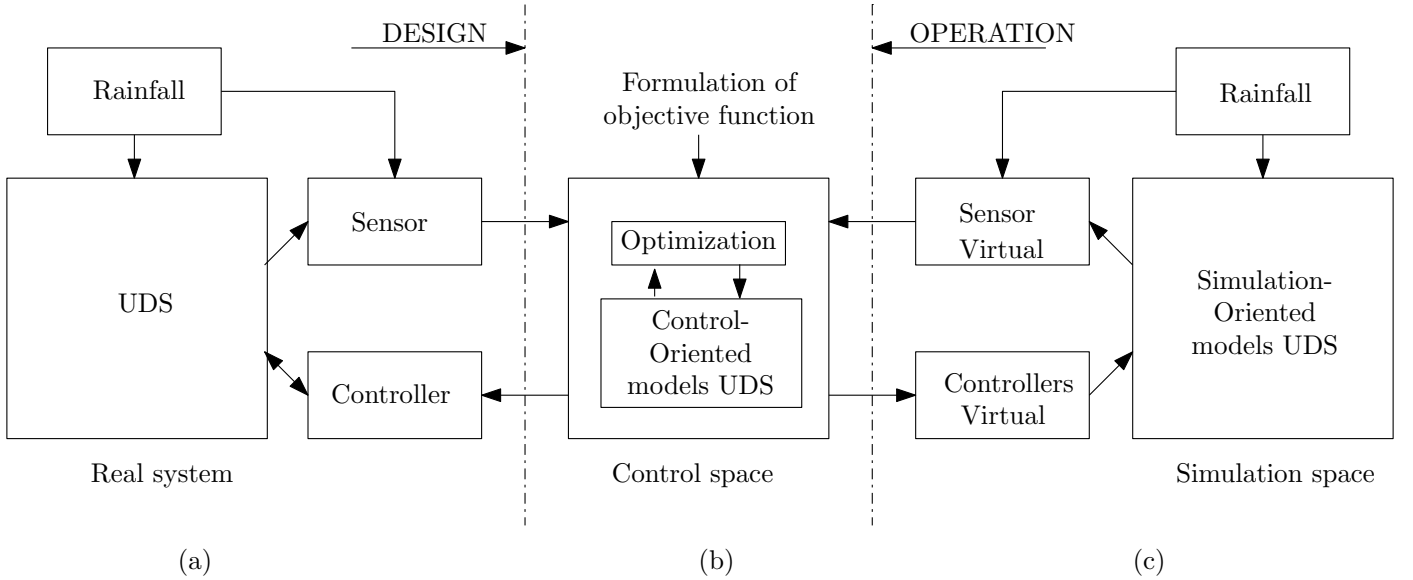Figure 4: Proposed taxonomy of modeling approaches for UDS.

Figure 5: Simulation-oriented model and control-oriented: (a) real system, (b) control space, and (c) simulation space model.

analysis of the transport model of sewage (i.e., characterizing the flow as a dynamic, diffusive, or kinematic wave). These mentioned simplifications are briefly explained next. The *kinematic wave* assumes that the flow is uniform, and that the friction slope is approximately equal to the slope of the channel. The *diffusive wave* describes a non–inertial behavior of the wave (i.e., sub–critical flow). The *dynamic wave* is valid for all the channel flow scenarios, and it uses all the terms of the SVE. In Table 5 some effects considered with each simplification of the SVE are summarized.

Some numerical methods have been developed in order to find the solution for SVE [12, 94, 95, 96]. These methods

are based on *finite elements*, and *finite differences* [81, 97, 98, 99]. A brief description of these methods is given next.

1. *Methods based on finite elements:* These methods have been used in a limited extension of the open-channel analysis. These methods do not offer any significant advantage in comparison with other methods for one–dimension flow problem, and difficulties have to be overcome when a shock or bore is formed in the solution [100]. Finite–element methods can be divided into explicit schemes such as Diffusive, Lax, Leap-Frog, Mc-Cormack, and Lambda [101]; and into implicit schemes such as Preissmann [77], Beam and warming, and Vasiliev [102, 103].

2. *Methods based on finite differences:* In the implicit finite–difference schemes, the spatial partial derivatives and/or the coefficients are replaced in terms of the values at the unknown time level. The unknown variables, therefore, appear implicitly in the algebraic equations. The algebraic equations for the entire system should be solved simultaneously in these methods. Several implicit finite–difference schemes have been used for the analysis of unsteady open–channel flows [104, 101].

Finally, Table 6 shows a categorization of both transport and integral models, as well as references of some cases where the modelling approaches have been used in UDS.

3.2. Control–Oriented Models

This subsection focuses on the presentation of the main control–oriented models, taking into account the compromise between accuracy and complexity. A classification of control–oriented models on data-driven, conceptual, and based on the linearization of SVE is proposed and discussed next.

3.2.1. Data–Driven approaches

Data-driven models are related to a set of techniques that are constructed and updated by using available information about the system. This information can be obtained either by simulation or from both measurement and historical data. It is important to clarify that it is more common to obtain the data-driven model by using measured data, and that despite the accelerated development of software tools to simulate these kind of complex systems, the use of simulation data to obtained a data-driven model is not usual. These models include different categories, generally divided into statistical and soft–computing models. Data–driven models are accurate, precise, and flexible, which make them able to handle UDS with different degrees of complexity based on the level of knowledge about a system. The use of data–driven approaches depends on the availability and quality of data from UDS. Therefore, the data–driven approach for modeling of UDS is viable whenever there exists a gradual development and implementation of monitoring systems in UDS (i.e., communication networks and sensors) with an appropriate relation of reliability, efficiency, and cost. In [107], the physically–based model and the data–driven model are compared, showing technical possibilities of the data-driven approach. In [111], some strategies of data–driven modeling, in water resources and environmental engineering applications using Matlab, are presented.

One proper approach for the data-driven control-oriented models generation, is the artificial neural networks (ANN) training. This approach has been widely used since it allows to fit a neural structure with the dynamical behavior of a system by measuring data. For instance, in [112] the ANN approach is presented as an alternative of data-driven models, and the development of the radar pluvial flooding identification for drainage systems allows to predict urban flooding in real time. Moreover, the use of measurements through rainfall radars to develop a data-driven models to train an ANN is introduced in [113]. These data presented in [113] are obtained from real CSO for a catchment in the North of England, UK.

In [114] a graph-theoretical-model approach is proposed, and the control of the sewer network is made with on/off actions over the system. This model is considered to be a data-driven model since measurements about some parameters are enough in order to solve the optimization problem that returns the control actions. For instance, for different control actions, it is required to dispose of information about pollutant loads in CSO events. Furthermore, measurements about run-off entering the sewer and dry weather flow are also needed.

3.2.2. Conceptual Models

An UDS conceptual model is made of a composition of concepts, which are used to analyze in an easy and fast way the UDS. In this review, the conceptual models are: the virtual–tank based model, the Nash model, the Muskingum model, and the integrator–delay model. It is worthwhile to highlight that all of these mentioned models only differentiate each other in the way the tanks are parametrized, and they are explained next.

1. The virtual–tanks model is based on the idea of sub–dividing the network. The division is made by grouping sets of elements in the network and replacing them by interconnected virtual repositories. At each time instant, the stored volumes in all the gathered elements represent the volume of water contained in the corresponding virtual repository [115]. Outflows are assumed to be nonlinear in [115], and linear with respect to tank volumes in [11]. The sewage volume is computed via the mass balance of the stored volume, the inflows, and the outflows [10, 11]. This model has been successfully used in the design of MPC controllers for UDS [53, 75, 80].

2. The Nash model is based on the idea of sub–dividing the network into sections. These sections are considered as several tanks in cascade, and the output of

Table 5: Simplification of the De Saint-Venant Equations.

Effects considered	Dynamic wave	Diffusive wave	Kinematic wave
Backwater effects and flow reversal	Yes	Yes	Yes
Attenuation of flood waves	Yes	Yes	No
Account for flow acceleration	Yes	No	No

Table 6: An overview of models for UDS.

Modeling of UDS			
Transport models	**Integrated models**		
[4] [12] [31] [56] [86] [93] [95] [99] [105] [106] [107] [108] [109] [110]	**UDS, RWB and WWTP** [84] [85]	**Physical and social variables** [86]	**Transport and infiltration** [87] [88]

each tank is the input of the following one [56, 92].

3. The Muskingum model is a method of lumped parameters, which describes the linear relationship between the inflow and the outflow affecting the corresponding volume [94]. The Muskingum model is a hydrological model widely used for simulation and control, due to its simplicity and its suitability in obtaining results for prediction. The Muskingum model has been used for designing MPC controllers as reported in [58, 82, 116]. Notice that the effectiveness of the Muskingum model depends on the estimation of its parameters. In [110], an optimal parameter estimation of Muskingum model using a modified particle–swarm algorithm is presented.

4. The integrator–delay model is composed by two parameters: an integrator, and a delay. This model is an approximation that relates backwater effects when a tank-delay model is used. In [109], a comparative study between Muskingum and integrator-delay models is presented.

3.2.3. Models Based on Linearization of the De Saint-Venant Equations

Conventional modeling methods are quite time consuming and cumbersome. That is why a simplified approach based on transfer function formulation of SVE has been proposed [76]. The SVE can be linearized around a steady–state equilibrium (Q_0, Y_0), where Q_0 defines the steady–state equilibrium for flows, and Y_0 defines the steady–state equilibrium for tank levels [93]. Another linearization of the SVE, is the one represented in the Laplace domain. This model has been validated through laboratory experiments by testing different flow conditions [108]. For instance, the Hayami model is the linearization of the difusive wave equation with the hypothesis that the celerity and difusivity are constant [117]. One way to obtain a simple linear model from the Hayami equation is the momentum matching method described in [74, 118]. In [119], two control strategies based on the Hayami model are compared and studied for open-channel systems.

3.3. Simulation Tools for Urban Drainage System

Since available software tools consider different models, this section presents a classification of simulation tools commonly used in the UDS framework. In accordance to the purpose of the UDS, software tools can be divided into two main categories:

1. Offline design and simulation.
2. Simulation tools for real–time control design.

3.3.1. Offline Design and Simulation

In [86], a complete review of software tools used on UDS is presented. Tools are classified into: 1) *integrated component-based models* (ICBMs); 2) *integrated urban drainage models* (IUDMs) or *integrated water supply models* (IWSMs); 3) *integrated urban water cycle models* (IUWCMs); and 4) *integrated urban water system models* (IUWSMs). ICBMs are the lowest level of integration, focusing on the components within the local urban water subsystem. IUDMs or IWSMs cover the integration of subsystems either of urban drainage or water supply, and particularly in process of treatment and transport. IUWCMs links IUDMs and IWSMs in a common framework. IUWSMs are the highest level of integration that combines the different urban water infrastructures with aspects such as weather and economy. Integrated models will play an important role in the design, simulation, and RTC of UDS, with the fast improvement of the simulation tools for UDS and its computational efficiency.

3.3.2. Simulation Tools for Real–Time Control design

In [92], a comparison between some software packages considering RTC in UDS is presented. Several features such as the type of model used by the software tool (e.g., Muskingum, SVE-based, Nash models), solution method used (based on finite differences or finite elements), and

the ability of applying control actions, among others, are taken into account.

In Table 7, some software tools used in the design of control strategies are presented, all af them being able to perform RTC (i.e., the capability to get in touch with a SCADA in order to read and write data from a database), and to establish an on-line connection between the software tool and another software tool for control.

Table 7: Software tools for RTC of USD.

Software tool	Reference
Mouse	[120]
Infoworks	[121]
Coral	[79]
Csoft	[116]
XPstorm	[122]
Swmm	[123]
Hystem-Extran	[124]
WEST	[125]
CityDrain	[126]

4. Conclusions

In this paper, some relevant RTC strategies applied to UDS are presented and briefly discussed, which can be divided into optimization-based and heuristic-based algorithms. Moreover, some relevant modeling approaches commonly used for UDS are also reviewed, proposing a taxonomy of UDS models (simulation–oriented and control–oriented), and discussing the run-time and complexity of the considered UDS models. The most relevant software tools used to simulate and to control UDS are also presented.

Based on the review made about RTC strategies applied to UDS, MPC has shown to be the most successful technique applied so far, because of its versatility to handle multi-variable complex systems and because it takes into account constraints and multiple control objectives. This technique is particularly suitable for its application in UDS. However, MPC requires a model, which is not an easy task for large-scale complex systems. On the other hand, rule-based and fuzzy logic control approaches have as an advantage that they do not require a model, but the expert knowledge about the general behavior of the system. Besides, these model-free approaches cannot consider formally an objective to minimize, and any desired performance should be achieved by rules of the form "if-then".

Furthermore, the control approaches that consider global and local objectives, differ in the sense that they require a different amount of information about the system. For instance, the centralized control schemes dispose of more information about the whole system, and they could consider both local and global objectives. Contrary, if only local objectives are desired to be consider in a system, then it is suitable to implement non-centralized control strategies. Additionally, the centralized scheme demands a communication structure that is expensive in comparison to the communication structure for the non-centralized control approach. Regarding the software tools, the literature review has shown that there are many and different software tools to design and simulate UDS.

References

[1] M. J. Hammond, A. S. Chen, S. Djordjevic, D. Butler, O. Mark, Urban flood impact assessment: A state of the art review, Urban Water Journal 1 (2013) 1–16.

[2] K. Berggren, M. Olofsson, M. Viklander, G. Svensson, A.-M. Gustafsson, Hydraulic impacts on urban drainage systems due to changes in rainfall caused by climatic change, Journal of Hydrologic Engineering 17 (1) (2011) 92–98.

[3] C. R. Jacobson, Identification and quantification of the hydrological impacts of imperviousness in urban catchments: A review, Journal of Environmental Management 92 (6) (2011) 1438 – 1448.

[4] T. Fletcher, H. Andrieu, P. Hamel, Understanding, management and modelling of urban hydrology and its consequences for receiving waters: A state of the art, Advances in Water Resources 51 (2013) 261 – 279, 35th Year Anniversary Issue.

[5] A. Semadeni-Davies, C. Hernebring, G. Svensson, L.-G. Gustafsson, The impacts of climate change and urbanisation on drainage in Helsingborg, Sweden: Combined sewer system, Journal of Hydrology 350 (1) (2008) 100–113.

[6] S. Todeschini, S. Papiri, C. Ciaponi, Performance of stormwater detention tanks for urban drainage systems in northern Italy, Journal of Environmental Management 101 (2012) 33 – 45.

[7] J. Marsalek, Review of stormwater source controls in urban drainage, in: J. Marsalek, E. Watt, E. Zeman, H. Sieker (Eds.), Advances in Urban Stormwater and Agricultural Runoff Source Controls, Vol. 6 of NATO Science Series, Springer Netherlands, 2001, pp. 1–15.

[8] S. Spatari, Z. Yu, F. A. Montalto, Life cycle implications of urban green infrastructure, Environmental Pollution 159 (8) (2011) 2174–2179.

[9] J. Foster, A. Lowe, S. Winkelman, The value of green infrastructure for urban climate adaptation, Tech. rep., Center for Clean Air Policy (February 2011).

[10] G. Cembrano, J. Quevedo, M. Salamero, V. Puig, J. Figueras, J. Martí, Optimal control of urban drainage systems. a case study, Control Engineering Practice 12 (1) (2004) 1–9.

[11] C. Ocampo-Martinez, Model Predictive Control of Wastewater Systems, Springer Verlag, London, 2011.

[12] D. Butler, J. Davies, Urban drainage, CRC Press, Denver, 2010.

[13] P. Borsanyi, L. Benedetti, G. Dirckx, W. De Keyser, D. Muschalla, A.-M. Solvi, V. Vandenberghe, M. Weyand, P. A. Vanrolleghem, Modelling real-time control options on virtual sewer systems, Journal of Environmental Engineering and Science 7 (4) (2008) 395–410.

[14] T. Beeneken, V. Erbe, A. Messmer, C. Reder, R. Rohlfing, M. Scheer, M. Schuetze, B. Schumacher, M. Weilandt, M. Weyand, Real time control (RTC) of urban drainage systems - A discussion of the additional efforts compared to conventionally operated systems, Urban Water Journal 10 (5) (2013) 293–299.

[15] D. G. Jamieson, U. Shamir, F. Martinez, M. Franchini, Conceptual design of a generic, real-time, near-optimal control system for water-distribution networks, Journal of Hydroinformatics 9 (1) (2007) 3–14.

[16] M. Schütze, A. Campisano, H. Colas, P. Vanrolleghem, W. Schilling, Real-time control of urban water systems, in: Proceedings of the International Conference on Pumps, Electromechanical Devices and Systems Applied to Urban Water Management. Valencia (Spain), 2003, pp. 1–19.

[17] EPA, Real time control of urban drainage networks, Tech. Rep. EPA/600/R-06/120, United States Environmental Protection Agency (September 2006).

[18] W. Schilling, B. Andersson, U. Nyberg, H. Aspegren, R. W., P. Harremoes, Real time control of wastewater systems, Journal of Hydric Resources 34 (6) (1996) 785–797.

[19] V. Erbe, M. Schutze, U. Haas, Application of a guideline document for sewer system real time control, in: Proceedings of NOVATECH 2007 - Sixth International Conference on Sustainable Techniques and Strategies in Urban Water Management. Lyon (France), 2007, pp. 761–768.

[20] G. Dirckx, M. Schuetze, S. Kroll, C. Thoeye, G. De Gueldre, B. Van De Steene, RTC versus static solutions to mitigate CSO's impact, in: Proceedings of the 12th International Conference on Urban Drainage. Porto Alegre (Brazil), 2011, pp. 10–15.

[21] E. Villeneuve, N. Jolicoeur, M. Pleau, C. Marcoux, R. Field, M. Stinson, The choice of a real-time control strategy for combined sewer overflow control, in: Proceedings of Water Environment Federation Collection Systems Wet Weather Pollution Control: Looking into Public, Private, and Industrial Issues Conference, 2000, pp. 7–10.

[22] D. Fiorelli, G. Schutz, Real-time control of a sewer network using a multi-goal objective function, in: Proceedings of the 17th Mediterranean Conference on Control & Automation. Thessaloniki (Greece), 2009, pp. 676–681.

[23] M. Marinaki, M. Papageorgiou, Optimal real-time control of sewer networks, Springer, London, 2005.

[24] P. Willems, T. B. Blanco, P.-K. Chiang, K. Cauwenberghs, J. Berlamont, B. De Moor, Real-time control of urban flooding, in: Proceedings of the International Conference on Water and Urban Development Paradigms: Towards an integration of engineering, design and management approaches. Leuven (Belgium), 2008, pp. 265–270.

[25] D. Muschalla, Optimization of integrated urban wastewater systems using multi-objective evolution strategies, Urban Water Journal 5 (1) (2008) 57–65.

[26] V. Gamerith, G. Gruber, D. Muschalla, Single-and multievent optimization in combined sewer flow and water quality model calibration, Journal of Environmental Engineering 137 (7) (2011) 551–558.

[27] A. Campisano, J. C. Ple, D. Muschalla, M. Pleau, P. Vanrolleghem, Potential and limitations of modern equipment for real time control of urban wastewater systems, Urban Water Journal 10 (5) (2013) 300–311.

[28] N. Kokash, An introduction to heuristic algorithms, Department of Informatics and Telecommunications, University of Trento, Italy 1 (2005) 10.

[29] R. S. Sánchez-Pena, F. D. Bianchi, Model selection: From LTI to switched-LPV, in: Proceedings of the American Control Conference. Montreal (Canada), 2012, pp. 1561–1566.

[30] K. Klepiszewski, T. Schmitt, Comparison of conventional rule based flow control with control processes based on fuzzy logic in a combined sewer system, Water Science and Technology 46 (6-7) (2002) 77–84.

[31] M. Schutze, D. Butler, B. M. Beck, Modelling Simulation and Control of Urban Wastewater Processes, Springer Verlag, London, 2002.

[32] M. Regneri, K. Klepiszewski, M. Ostrowski, P. A. Vanrolleghem, Fuzzy decision making for multi-criteria optimization in integrated wastewater system management, in: Proceedings of the 6th International Conference on Sewer Processes and Networks. Surfers Paradise (Australia), 2010, pp. 1–10.

[33] V. Nikolic, Z. Cojbasic, I. Ciric, E. Petrovic, Intelligent decision making in wastewater treatment plant SCADA system, Facta Universitatis, Series: Automatic Control and Robotics 9 (1) (2010) 69–77.

[34] W. Tang, Z. Wang, Q. Feng, M. Wang, Application of fuzzy expert control to APMP pulping wastewater treatment process of aerobic, in: Proceedings of the 2010 IEEE International Conference on Mechatronics and Automation. Xian (China), 2010, pp. 339–344.

[35] K. Seggelke, R. Lowe, T. Beeneken, L. Fuchs, Implementation of an integrated real-time control system of sewer system and waste water treatment plant in the city of Wilhelmshaven, Urban Water Journal 10 (5) (2013) 330–341.

[36] Y.-M. Chiang, L.-C. Chang, M.-J. Tsai, Y.-F. Wang, F.-J. Chang, Auto-control of pumping operations in sewerage systems by rule-based fuzzy neural networks, Hydrology & Earth System Sciences 15 (1) (2011) 185–196.

[37] W. B. Tagherouit, S. Bennis, J. Bengassem, A fuzzy expert system for prioritizing rehabilitation of sewer networks, Computer-Aided Civil and Infrastructure Engineering 26 (2) (2011) 146–152.

[38] L. Hu, H. Xia, H. Wang, Fuzzy control applied to drainage system of city highway tunnel, in: Proceedings of the II International Workshop on Education Technology and Computer Science. Los Angeles (USA), Vol. 3, 2010, pp. 810–813.

[39] B. Joseph, M. Jung, C. Ocampo-Martinez, S. Sager, G. Cembrano., Minimization of sewage network overflow, Water Resources Management 28 (1) (2014) 41–63.

[40] G. Shah, S. Engell, Tuning MPC for desired closed-loop performance for MIMO systems, in: Proceedings of the American Control Conference. San Francisco (USA), 2011, pp. 4404–4409.

[41] G. Fu, D. Butler, S.-T. Khu, Multiple objective optimal control of integrated urban wastewater systems, Environmental Modelling & Software 23 (2) (2008) 225–234.

[42] J. Branke, K. Deb, K. Miettinen, R. Slowinski, Multiobjective optimization: interactive and evolutionary approaches, Springer Verlag, London, 2008.

[43] D. E. Kirk, Optimal control theory: an introduction, Courier Dover Publications, Mineola, New York, 2012.

[44] M. Marinaki, M. Papageorgiou, Linear-quadratic regulators applied to sewer network flow control, in: Proceedings of the European Control Conference. Cambridge (United Kingdom), 2003, pp. 1–4.

[45] J. Lemos, L. Pinto, Distributed linear-quadratic control of serially chained systems: Application to a water delivery canal, IEEE Control Systems Magazine 32 (6) (2012) 26–38.

[46] J. M. Sousa, U. Kaymak, Fuzzy Decision Making in Modeling and Control, World Scientific Publishing Co. Pte. Ltd, New Jersey, 2002.

[47] T. Bernard, M. Sajidman, H.-B. Kuntze, A New Fuzzy-Based Multi-Objective Optimization Concept for Process Control Systems, Springer, Heidelberg, Berlin, 2001.

[48] M. Aulinas, J. C. Nieves, U. Cortés, M. Poch, Supporting decision making in urban wastewater systems using a knowledge-based approach, Environmental Modelling & Software 26 (5) (2011) 562–572.

[49] M. Marinaki, Wastewater System, Optimization of, in: Encyclopedia of Optimization, Springer, 2009, pp. 4055–4060.

[50] J. H. Cho, K. Seok Sung, S. Ryong Ha, A river water quality management model for optimising regional wastewater treatment using a genetic algorithm, Journal of Environmental Management 73 (3) (2004) 229–242.

[51] R. Toro, C. Ocampo-Martinez, F. Logist, J. Van Impe, V. Puig, Tuning of predictive controllers for drinking water networked systems, in: Proceedings of the 18th IFAC world congress. Milano (Italy), 2011, pp. 14507–14512.

[52] A. Venkat, I. Hiskens, J. Rawlings, S. Wright, Distributed MPC strategies with application to power system automatic generation control, IEEE Transactions on Control Systems Technology 16 (6) (2008) 1192–1206.

[53] C. Ocampo-Martinez, V. Puig, G. Cembrano, J. Quevedo, Application of predictive control strategies to the management of complex networks in the urban water cycle, IEEE Control Systems Magazine 33 (1) (2013) 15–41.

[54] C. Ocampo-Martinez, A. Ingimundarson, V. Puig, J. Quevedo, Objective prioritization using lexicographic minimizers for MPC of sewer networks, IEEE Transactions on Control Systems Technology 16 (1) (2008) 113–121.

[55] J. M. Maciejowski, Predictive Control with Constraints, Pren-

tices Hall, London, 2002.

[56] M. Regneri, K. Klepiszewski, S. Seiffert, P. Vanrolleghem, M. Ostrowski, Transport sewer model calibration by experimental generation of discrete discharges from individual CSO structures, in: Proceedings of the 2012 International Congress on Environmental Modelling and Software Managing Resources of a Limited Planet. Leipzig (Germany), 2012, pp. 3109–3116.

[57] S. Heusch, J. Hild, G. Leugering, M. Ostrowski, Performance and comparison of BlueM.MPC and Lamatto, in: Mathematical Optimization of Water Networks, Springer Basel, 2012, pp. 151–165.

[58] J. Giraldo, S. Leirens, M. Díaz-Granados, J. Rodríguez, Nonlinear optimization for improving the operation of sewer systems: the Bogotá case study. International Environmental Modelling and Software Society (iEMSs), in: Proceedings of the International Congress on Environmental Modelling and Software Modelling for Environments Sake, Fifth Biennial Meeting. Ottawa (Canada), 2010, pp. 1–8.

[59] K.-J. Van Heeringen, J. Gooijer, D. Schwanenberg, Practical application of drainage system control by using MPC in Noorderzijlvest, in: Proceedings of the EGU General Assembly Conference. Vienna (Austria), Vol. 15, 2013, pp. 11965–11974.

[60] D. Mayne, J. Rawlings, C. Rao, P. Scokaert, Constrained model predictive control: Stability and optimality, Automatica 36 (6) (2000) 789–814.

[61] J. H. Lee, Model predictive control: review of the three decades of development, International Journal of Control, Automation and Systems 9 (3) (2011) 415–424.

[62] M. Lazar, W. Heemels, D. Muñoz De La Peña, T. Alamo, Further results on robust MPC using linear matrix inequalities, in: Nonlinear Model Predictive Control, Springer, 2009, pp. 89–98.

[63] J. S. Kim, Recent advances in adaptive MPC, in: Proceedings of the International Conference on Control, Automation and Systems. Gyeonggi-do (South Korea), 2010, pp. 218–222.

[64] A. J. D. Real, A. Arce, C. Bordons, Combined environmental and economic dispatch of smart grids using distributed model predictive control, Electrical Power and Energy Systems 54 (2014) 65–76.

[65] T. Tettamanti, I. Varga, Distributed traffic control system based on model predictive control, Periodica Polytechnica Civil Engineering 54 (1) (2010) 3–9.

[66] F.-J. Sorcia-Vazquez, C.-D. Garcia-Beltran, G. Valencia-Palomo, G.-V. Guerrero-Ramirez, V.-M. Alvarado-Martinez, M. Adam-Medina, Control predictivo distribuido óptimo aplicado al control de nivel de un proceso de cuatro tanques acoplados, in: Proceedings of the Congreso Nacional de Control Automático. Ensenada (Mexico), 2013, pp. 729–734.

[67] C. Ocampo-Martinez, V. Puig, J. Grosso, S. Montes-de Oca, Multi-layer decentralized MPC of large-scale networked systems, in: Distributed Model Predictive Control Made Easy, Springer, 2014, pp. 495–515.

[68] S. Leirens, C. Zamora, R. R. Negenborn, B. De Schutter, Coordination in urban water supply networks using distributed model predictive control, in: Proceedings of the 2010 American Control Conference. Baltimore (USA), 2010, pp. 3957–3962.

[69] R. R. Negenborn, P. van Overloop, T. Keviczky, B. De Schutter, Distributed model predictive control of irrigation canals, Networks and Heterogeneous Media 4 (2) (2009) 359–380.

[70] P. D. Christofides, R. Scattolini, D. Muñoz de la Peña, J. Liue, Distributed model predictive control: A tutorial review and future research directions, Computers and Chemical Engineering 51 (5) (2013) 21–41.

[71] E. Ramirez-Llanos, N. Quijano, A population dynamics approach for the water distribution problem, International Journal of Control 83 (9) (2010) 1947–1964.

[72] J. Barreiro-Gomez, G. Obando, G. Riaño-Briceño, N. Quijano, C. Ocampo-Martinez, Decentralized control for urban drainage systems via population dynamics: Bogotá case study, in: European Control Conference, Linz, Austria, 2015.

[73] P. D. Taylor, L. B. Jonker, Evolutionary stable strategies and game dynamics, Mathematical Biosciences 40 (1978) 145–156.

[74] P. Malaterre, Modelisation, analysis and LQR optimal control of an irrigation canal, Ph.D. thesis, LAAS-CNRS-ENGREF-Cemagref (1994).

[75] C. Ocampo-Martinez, A. Ingimundarson, A. Bemporad, V. Puig, Suboptimal hybrid model predictive control: Application to sewer networks, in: Proceedings of the IFAC World Congress. COEX (South Korea), 2008, pp. 5264–5269.

[76] C. Lihui, X. Yugeng, L. Dewei, Aggregation-based model predictive control of open channel networks, in: Proceedings of the 29th Chinese Control Conference. Beijing (China), IEEE, 2010, pp. 3170–3175.

[77] P. Malaterre, J. Rodellar, Multivariable predictive control of irrigation canals. Design and evaluation on a 2-pool model, in: Proceedings of the International Workshop on Regulation of Irrigation Canals. Rabat (Marroco), 1997, pp. 230–238.

[78] P. J. Van Overloop, A. J. Clemmens, R. J. Strand, R. M. J. Wagemaker, E. Bautista, Real-time implementation of model predictive control on Maricopa-Stanfield irrigation and drainage district's WM canal, Journal of irrigation and drainage engineering 136 (11) (2010) 747–756.

[79] V. Puig, G. Cembrano, J. Romera, J.-J. Quevedo, B. Aznar, G. Ramón, J. Cabot, Predictive optimal control of sewer networks using CORAL tool: application to Riera Blanca catchment in Barcelona, Water Science & Technology 60 (4) (2009) 869–878.

[80] E. E. Visser, Model predictive control of wastewater systems, Master's thesis, University of Twente (2013).

[81] M. Xu, P. V. Overloop, N. van de Giesen, On the study of control effectiveness and computational efficiency of reduced Saint-Venant model in model predictive control of open channel flow, Advances in Water Resources 34 (2) (2011) 282 – 290.

[82] C. Zamora, J. M. Giraldo, S. Leirens, Model predictive control of water transportation networks, in: Proceedings of the ANDESCON. Bogota (Colombia), 2010, pp. 1–6.

[83] W. Barreto, Z. Vojinovic, R. Price, D. Solomatine, Multiobjective evolutionary approach to rehabilitation of urban drainage systems., Journal of Water Resources Planning and Management 136 (5) (2010) 547–554.

[84] A. Elliott, S. Trowsdale, A review of models for low impact urban stormwater drainage, Environmental Modelling & Software 22 (3) (2007) 394–405.

[85] G. Freni, M. Maglionico, G. Mannina, G. Viviani, Comparison between a detailed and a simplified integrated model for the assessment of urban drainage environmental impact on an ephemeral river, Urban Water Journal 5 (2) (2008) 21 – 31.

[86] P. M. Bach, W. Rauch, P. S. Mikkelsen, D. T. McCarthy, A. Deletic, A critical review of integrated urban water modelling urban drainage and beyond, Environmental Modelling & Software 54 (2014) 88–107.

[87] J. Henonin, B. Russo, O. Mark, P. Gourbesville, Real-time urban flood forecasting and modelling – a state of the art, Journal of Hydroinformatics 15 (3) (2013) 717 – 736.

[88] C. Nasello, T. Tucciarelli, Dual multilevel urban drainage model, Journal of Hydraulic Engineering 131 (9) (2005) 748 – 754.

[89] G. Mannina, G. Viviani, Receiving water quality assessment: comparison between simplified and detailed integrated urban modelling approaches, Water Science and Technology 62 (10) (2010) 2301–2312.

[90] V. Te Chow, Open channel hydraulics, McGraw-Hill Book Company, Inc, New York, 1959.

[91] A. Mailhot, S. Duchesne, Design criteria of urban drainage infrastructures under climate change, Journal of Water Resources Planning and Management 136 (2) (2009) 201–208.

[92] L. A. Garcia-Gutierrez, E. Escobar, J. Barreiro-Gomez, N. Quijano Silva, C. Ocampo-Martinez, D. Tellez, On the modeling and real-time control of urban drainage systems: A survey, in: Proceedings of the 11th International Conference on Hydroinformatics. New York (USA), 2014, pp. 1–8.

[93] X. Litrico, V. Fromion, Modeling and Control of Hydrosystems, Springer, London, 2009.

[94] J. Cunge, F. Holly, A. Verwey, Practical aspects of computational river hydraulics, Pitman publishing, London, 1980.

[95] P. García Navarro, E. Playán Jubillar, et al., Numerical modelling of hydrodynamics for water resources, Taylor & Francis, Zaragosa, 2007.

[96] T. Hvitved-Jacobsen, J. Vollertsen, A. H. Nielsen, Sewer processes: microbial and chemical process engineering of sewer networks, CRC press, Florida, 2013.

[97] T. Strelkoff, Numerical solution of Saint-Venant's Equations, Journal of the Hydraulics Division 96 (1) (1970) 223–252.

[98] X. Zhuan, X. Xia, Models and control methodologies in open water flow dynamics: A survey, in: Proceedings of the AFRICON. Windhoek (South Africa), 2007, pp. 1–7.

[99] M. Xu, R. Negenborn, P. Van Overloop, N. Van de Giesen, De Saint-Venant equations-based model assessment in model predictive control of open channel flow, Advances in Water Resources 49 (2012) 37 – 45.

[100] F. Zarmehi, A. Tavakoli, M. Rahimpour, On numerical stabilization in the solution of Saint-Venant equations using the finite element method, Computers & Mathematics with Applications 62 (4) (2011) 1957–1968.

[101] R. Szymkiewicz, Numerical modeling in open channel hydraulics, Springer, New York, 2010.

[102] R. Szymkiewicz, Finite-element method for the solution of the Saint-Venant equations in an open channel network, Journal of hydrology 122 (1) (1991) 275–287.

[103] A. Tavakoli, F. Zarmehi, Adaptive finite element methods for solving Saint-Venant's equations, Scientia Iranica 18 (6) (2011) 1321 – 1326.

[104] R. Garcia, R. A. Kahawita, Numerical solution of the Saint-Venant equations with the MacCormack finite-difference scheme, International Journal for Numerical Methods in Fluids 6 (5) (1986) 259–274.

[105] L. Benedetti, J. Langeveld, A. Comeau, L. Corominas, G. Daigger, C. Martin, P. S. Mikkelsen, L. Vezzaro, S. Weijers, P. A. Vanrolleghem, Modelling and monitoring of integrated urban wastewater systems: review on status and perspectives, Water Science and Technology 68 (6) (2013) 1203–1215.

[106] M. Kleidorfer, Uncertain calibration of urban drainage models, a scientific approach to solve practical problems, Ph.D. thesis, Universitat Innsbruck (2009).

[107] J. Ten Veldhuis, S. Tait, Data-driven urban drainage analysis: an alternative to hydrodynamic models?, in: Proceedings of the 12nd International Conference on Urban Drainage. Porto Alegre (Brazil), Vol. 101, 2011, pp. 33–45.

[108] P. Sreeja, K. Gupta, Transfer function formulation of Saint-Venant's equations for modeling drainage channel flow: An experimental evaluation, Water Resources Management 22 (12) (2008) 1881–1898.

[109] Y. Bolea, V. Puig, A. Grau, Discussion on Muskingum versus integrator-delay models for control objectives, Journal of Applied Mathematics 2014 (2014) 11–15.

[110] W. Wang, Y. Kang, L. Qiu, Optimal parameter estimation for Muskingum model using a modified particle swarm algorithm, in: Proceedings of the Third International Joint Conference on Computational Science and Optimization. Huangshan, Anhui (China), Vol. 2, 2010, pp. 153–156.

[111] S. Araghinejad, Data-Driven Modeling: Using MATLAB in Water Resources and Environmental Engineering, Springer, New Delhi, 2014.

[112] A. P. Duncan, A. S. Chen, E. C. Keedwell, S. Djordjević, D. A. Savić, RAPIDS: early warning system for urban flooding and water quality hazards, in: Machine Learning in Water Systems Symposium: Part of AISB Annual Conference, 2013, pp. 1–5.

[113] S. R. Mounce, W. Shepherd, G. Sailor, J. Shucksmith, A. Saul, Predicting CSO chamber depth using artificial neural networks with rainfall radar data, IWA Water Science and Technology 6 (69) (2014) 1326–1333.

[114] R. R. Van Nooijen, A. Kolechkina, Speed of discrete optimisation solvers for real time sewer control, Water Science and Technology 10 (5) (2013) 354–363.

[115] M. S. Gelormino, N. Ricker, Model-predictive control of a combined sewer system, International Journal of Control 59 (3) (1994) 793–816.

[116] O. Fradet, M. Pleau, A. Desbiens, H. Colas, Theoretical and field validation of solutions based on simplified hydraulic models for the real-time control of sewer networks, NOVATECH 2010 1 (2010) 10–20.

[117] S. Hayami, On the propagation of flood waves, Bulletins-Disaster Prevention Research Institute, Kyoto University 1 (1951) 1–16.

[118] X. Litrico, D. Georges, Robust continuous-time and discrete-time flow control of a dam–river system.(I) modelling, Applied mathematical modelling 23 (11) (1999) 809–827.

[119] E. Duviella, V. Puig, P. Charbonnaud, T. Escobet, F. Carrillo, J. Quevedo, Supervised gain-scheduling multimodel versus linear parameter varying internal model control of open-channel systems for large operating conditions, Journal of Irrigation and Drainage Engineering 136 (8) (2010) 543–552.

[120] V. Nilsen, J. Lier, J. Bjerkholt, O. Lindholm, Analysing urban floods and combined sewer overflows in a changing climate, Journal of water and climate change 2 (4) (2011) 260–271.

[121] M. Le Quiniou, P. Mandel, L. Monier, Optimization of drinking water and sewer hydraulic management: Coupling of a genetic algorithm and two network hydraulic tools, Procedia Engineering 89 (2014) 710–718.

[122] F. Akram, M. G. Rasul, M. M. K. Khan, M. S. I. I. Amir, Comparison of different hydrograph routing techniques in XP-STORM modelling software: A case study, World Academy of Science, Engineering and Technology International Journal of Environmental, Ecological, Geological and Mining Engineering 8 (3) (2014) 208–218.

[123] G. Burger, R. Sitzenfrei, M. Kleidorfer, W. Rauch, Parallel flow routing in SWMM 5, Environmental Modelling & Software 53 (2014) 27–34.

[124] M. Pabst, J. Alex, M. Beier, C. Niclas, M. Ogurek, D. Peikert, M. Schütze, ADESBA-A new general global control system applied to the Hildesheim sewage system, in: Proceedings of the 12th international conference on urban drainage. Porto Alegre (Brazil), 2011, pp. 1–8.

[125] H. Vanhooren, J. Meirlaen, Y. Amerlinck, F. Claeys, WEST: modelling biological wastewater treatment, Journal of Hydroinformatics 1 (5) (2003) 27–50.

[126] S. Achleitner, M. Marderl, W. Rauch, City drain: An open source approach for simulation of integrated urban drainage systems, Environmental Modelling & Software 22 (2007) 1184 – 1195.