Modeling and Control in Open-Channel Irrigation Systems: A review⋆

Gregory Conde[a,b,c], Nicanor Quijano[a] and Carlos Ocampo-Martinez[b]

[a] *School of Engineering, University of Los Andes, Bogotá, Colombia. Email: nquijano@uniandes.edu.co*
[b] *Automatic Control Department, Universitat Politècnica de Catalunya, Institut de Robòtica i Informàtica Industrial (CSIC-UPC) Barcelona, Spain. Email: carlos.ocampo@upc.edu*
[c] *School of Engineering, Universidad Central, Bogotá, Colombia. Email: gcondem@ucentral.edu.co*

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ABSTRACT

Water is the most important element of food production, and the easiest and most cost-efficient way to transport it is through open-channel irrigation systems (OCIS). These types of systems have a high agricultural and ecological impact. However, in most countries, OCIS lack automation and efficiency at mitigating the economic and environmental costs that the waste of water is causing. In order to identify modeling strategies and the best control practices, this paper presents an overview of the main factors of control-oriented models and control strategies for OCIS. In modeling, two fields are considered: i) models that come from simplifications of the Saint-Venant Equations (SVE); and ii) approximate models. For each category, a brief description of the control-oriented modeling strategies is given. In the control field, five relevant aspects are considered: i) centralized, decentralized, and distributed architectures; ii) control objectives; iii) regulation structures and control-action variables; iv) feedback and feedforward configurations; and v) control strategies. For each aspect, the most important features are explained. Finally, with the aim of establishing the acceptability of the reported modeling and control techniques, as well as challenges that remain open, a discussion and a case study are presented.

1. Introduction

Through irrigation, it is possible to compensate the amount of water that crops need in dry seasons and to extend the productive land away from natural water sources. The easiest and most economical way to transport water in agriculture is through open-channels. Currently, water is taken from rivers and transported by using an intricate network of channels to each user. These networks are called open-channel irrigation systems (OCIS). Nearly 70% of the water consumed in the world is used for irrigation (OECD, 2018), and most of the water is transported through open-channels. Moreover, the world population grows continuously. In 1980, the world population was around 4.4 billion. Now, there are about 7.4 billion people and in 2060 the population will likely increase to 10.2 billion (United Nations Department of Economic and Social Affairs Population Division, 2017). Consequently, in 40 years food production must increase by 40%.

On the other hand, the irrigation process has a high environmental impact since the water taken from a river reduces its flow, affecting life in the river and the surrounding ecosystem. Therefore, as it is highlighted by Lamnabhi-Lagarrigue et al. (2017), it is necessary to develop new approaches to increase food production by increasing the efficiency of the OCIS, where "efficiency is seen as the ratio of the volume of water delivered to the users and the volume of water extracted from the source" (Mareels et al., 2005).

The OCIS are complex systems. In most countries, their operation is in charge of user associations, which maintain the system in operational conditions, manage the economic resources, and calculate, assign, and supply the appropriate amount of water to the users. The water assignment process can be performed in multiple modes such as: i) rotational mode, where the central administration develops the supply polices and allocates the amount of water and time duration of the flow delivered to each user; ii) on-request mode, where the user must request in advance the amount of hydraulic resource that will be used; and iii) on-demand mode, where the user is free to take water from the system when it is needed. According to the assignment process and the hydraulic characteristics of the system, the central administration must calculate the water levels and flows throughout the systems, which are regulated by gates and weirs, and their positions are calculated with the aim of assigning a specific amount of water to each user. Most of the OCIS operate in rotational and in on-request modes in absence of automatic control systems. Therefore, each regulation structure is manually adjusted by operators, who must carry out this task throughout many kilometers of channels and hundreds of regulation structures. In the normal operation of the OCIS it is common to find disturbances such as flow variation at the source, channel obstructions, leaks, overflows, and demand changes. These

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ORCID(s):

types of disturbances lead to water spillages that affect the OCIS efficiency (Litrico and Fromion, 2006a).

In order to promote the implementation of automatic control in OCIS, in the last three decades, multiple works that review the advances in modeling and control of OCIS have been reported. For instance, Malaterre (1995) presents an exhaustive characterization of regulation methods for OCIS, showing the need to unify definitions and concepts in a field where there is a convergence of civil, hydraulic, and control engineers. Schuurmans (1997) shows basic principles for understanding the control problem in OCIS, explaining the finite-difference model and proposing the integrator delay model to adjust the real dynamic behavior of OCIS in a simple way. Moreover, in the control area, Schuurmans (1997) presents the implementation of traditional controllers such as the linear quadratic regulator (LQR) and the linear quadratic Gaussian regulator (LQG). Malaterre et al. (1998) review and classify the implemented controllers according to the variables (controlled, measured, control-action), the logic of control (type and direction), and design technique. Furthermore, Malaterre and Baume (1998) explore several modeling techniques and control strategies. Mareels et al. (2005) and Cantoni et al. (2007) discuss some aspects such as infrastructure automation, control objectives, and system identification. Weyer (2008) shows alternatives in centralized and decentralized control. Moreover, Malaterre (2008) reviews the main concepts and strategies in the control of OCIS. Over the last decade, the task committee on recent advances in canal automation provides a practical guide on OCIS automation (Wahlin and Zimbelman, 2014). This guide covers topics about supervisory control and data acquisition, as well as fundamentals in the design and implementation of control strategies. Finally, Ding et al. (2018) provide a review focused on applications of model predictive control in agriculture, where it can be highlighted that the control of OCIS is the area that shows more development of this kind of control strategy.

According to the presented information, the OCIS control problem is an issue of interest, which has been continuously studied and summarized in several works. On the other hand, in control systems, usually, the selection of an accurate control-oriented model of the system is an important stage that must be addressed before selecting, designing, and implementing a control strategy. However, it has been identified that in the reported reviews, the control-oriented modeling topic has not been broadly addressed. Moreover, control of OCIS is a relevant and challenging field, where there is a continuous generation of contributions. Therefore, there is a need to: i) review recent modeling and control techniques that have been reported; ii) establish the acceptability of existent techniques; and iii) report challenges that remain open for future research.

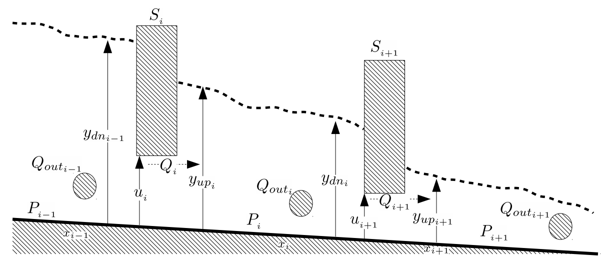

Fig. 1: Proposed representation for OCIS.

In this way, the motivation of this paper is to provide a detailed review[1] of modeling and control of OCIS towards providing useful information for researchers interested in contributing to the OCIS modeling and control area. This review focuses on the two main aspects in control of OCIS: control-oriented models and control design, which are firstly presented, subsequently discussed, and finally illustrated through a case study.

The remainder of the paper is organized as follows. Section 2 starts by presenting the proposed notation and a description of the OCIS. In Section 3, a classification of the control-oriented models for OCIS is given. In Section 4, the multiple approaches that in control of OCIS can be established are presented and classified. In Section 5, it is given a discussion around the reported modeling and control approaches for OCIS. In section 6, it is presented a case study that explains the development of the most common control-oriented modeling strategy, and the most common control strategies for OCIS. Finally, in Section 7, some conclusions are drawn.

2. Preliminaries

In the current framework, an open-channel is a structure used to transport water. Typically, open-channels present a trapezoidal shape, but there are channels with cylindrical, parabolic, rectangular, and irregular shapes. In the literature, there is not a unified notation for the inputs, outputs, and state variables of OCIS. In Fig.1, the proposed representation for OCIS is shown, and in Table 1 the variables are summarized. In this case, the channel $\boldsymbol{P}_i$ is fed by the flow $\boldsymbol{Q}_i$ that comes from the upstream channel $\boldsymbol{P}_{i-1}$. Besides, x_i is a position inside $\boldsymbol{P}_i$, from the upstream end of the channel, and y_{x_i} represents the depth at the x_i position. For control purposes, the most important output variables

[1]The principal database used in this survey is SCOPUS, which is known as one of the largest databases of peer-reviewed literature. In the selected database, the searching method has been performed around journals in control of open channels, which have been reported since 2007, with a specific search entry given by: "water," and "open channel control" or "canal control," selecting the works that discuss about modeling and control of OCIS. Additionally, books and previous seminal papers that contribute to the explanation of modeling and control strategies have been also included.

Table 1
Notation

P_i	The section between two consecutive cross structures (pool, channel, canal).
i	Stage number (1 = first channel)
Q_i	P_i inflow (m^3/s)
Q_{i+1}	P_{i+1} inflow and P_i outflow (m^3/s)
S_i	Cross structure that regulates the flow Q_i
u_i	regulation structure position (m)
x_i	Downstream distance from S_i (m)
y_{x_i}	Depth at a point x_i (m)
y_{up_i}	Depth at the upstream end of P_i (m)
y_{dn_i}	Depth at the downstream end of P_i (m)
Q_{out_i}	Outlet flow (m^3 /s)
W_{x_i}	Channel width at a point x_i (m)
L_i	Channel length (m)
q_{x_i}	Leak at a point x_i (m^3/s)

are the upstream and downstream depths of a channel, denoted by y_{up_i} and y_{dn_i}, respectively. From the channel P_i there could be multiple outflows to other channels or users. In Fig. 1, the outflows are simplified into an outlet flow Q_{out_i}, and the flow that feeds the downstream channel Q_{i+1}. The most notorious feature is that, in steady-state, the volume in a channel increases when the inflow increases, and decreases when the outflow increases. The flow Q_i has an hydraulic relationship with the regulation structures, and these structures can be divided into gates (Fig. 2) and weirs (Fig. 3), which can be in free-flow or submerged-flow (Litrico and Fromion, 2009). In Table 2, the mathematical relationships for the discharge through each type of regulation structure are presented, where u_i is the position of the regulation structure, w_i the width of the regulation structure, g the gravity constant, and C_{d_i} the discharge coefficient.

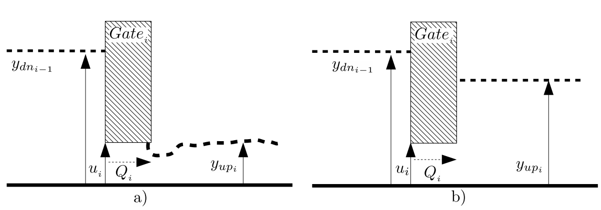

Fig. 2: Flow relation for: a) Gate in free-flow. b) Gate in submerged-flow.

3. Modeling

A control-oriented model is a mathematical representation of a system that is used for the description, explanation, and prediction of its behavior, which

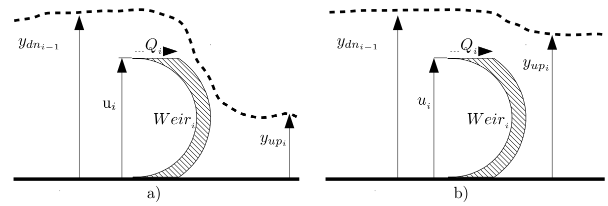

Fig. 3: Flow relation for: a) Weir in free-flow. b) Weir in submerged-flow.

Table 2
Flow relation for different categories of regulation structures

	Free-flow	Submerged-flow
Gate	$Q_i = Cd_i w_i u_i \sqrt{2g}\sqrt{y_{dn_{i-1}} - 0.5u_i}$	$Q_i = Cd_i w_i u_i \sqrt{2g}\sqrt{y_{dn_{i-1}} - y_{up_i}}$
Weir	$Q_i = Cd_i w_i \sqrt{2g}(y_{dn_{i-1}} - u_i)^{3/2}$	$Q_i = Cd_i w_i \sqrt{2g}(y_{dn_{i-1}} - y_{up_i})^{3/2}$

helps to understand its dynamics and design control systems with the aim of reaching a desirable performance. Obtaining control-oriented models for OCIS is an aspect that has a high number of alternatives and there is not a final rule for choosing a modeling methodology. In 1871, Adhemar Jean Claude Barre de Saint-Venant proposed appropriate simplifications to adjust the Navier-Stokes equations to channels and derived the Saint-Venant equations (Darrigol, 2006), which describe the dynamics of infinitesimal flow in one direction. Since then, the Saint-Venant equations (SVE) have been the most used mathematical tool for modeling open-channels and rivers. The SVE are two non-linear partial differential equations given by

$$W_{x_i}\frac{\partial y_{x_i}}{\partial t} = -\frac{\partial Q_{x_i}}{\partial x} - q_{x_i}, \tag{1a}$$

$$\frac{\partial Q_{x_i}}{\partial t} = -2\beta\frac{Q_{x_i}}{A_{x_i}}\frac{\partial Q_{x_i}}{\partial x} + \beta W_{x_i}\frac{{Q_{x_i}}^2}{{A_{x_i}}^2}\frac{\partial y_{x_i}}{\partial x} - \frac{\left|Q_{x_i}\right| Q_{x_i} g n^2}{A_{x_i}{R_{x_i}}^{4/3}} + g\left(I - \frac{\partial y_{x_i}}{\partial x}\right)A_{x_i}, \tag{1b}$$

where (1a) is related to mass conservation, and (1b) is related to momentum conservation. Moreover, W_{x_i} is the channel width, q_{x_i} is a variable associated with leaks, β is a momentum correction coefficient, A_{x_i} is the wetted surface, R_{x_i} is the hydraulic radius, I is the channel's slope, and n is the Manning's resistance coefficient. The variables y_{x_i} and Q_{x_i} are related to depth and flow, respectively (Chaudhry, 2008; Schuurmans, 1997). The direct use of the SVE for control systems design is impractical (Rabbani et al., 2010), and this affirmation can be corroborated analyzing the works reported by Liu et al. (1995) and Dos Santos and Prieur (2008), where the development of control strategies using the non-linear partial SVE shows unsystematic procedures. Therefore, in the literature, there are multiple types of control-oriented models that describe the dynamics of irrigation channels and, as shown in Fig. 4, these models can be classified into two fields: i) models that come from analytical simplifications of the SVE; and, ii) models that come from approximations, observations, and assumptions of the dynamic behavior of the OCIS.

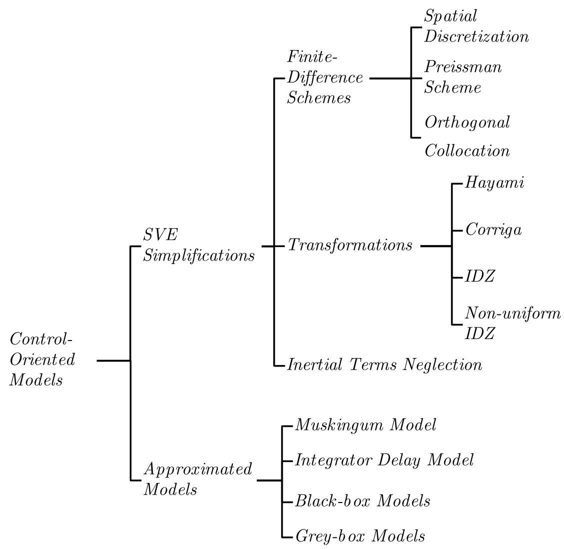

Fig. 4: Classification of control-oriented models for OCIS.

3.1. Models obtained from simplifications of the SVE

These models could be divided into three subgroups. In the first group, for the linearized and non-linearized SVE, explicit and implicit finite-difference schemes are proposed. Balogun et al. (1988) present an explicit spatial discretization of the SVE where each channel is divided into sections, and for each section one differential equation for depth and another differential equation for flow are obtained. The weakness of this kind of discretized models is that their stability depends on the discretization step size. Therefore, in order to obtain a stable control-oriented model, the obtained model has a high order. this modeling strategy is used in several reported works (e.g., Reddy 1990b; Garcia et al. 1992; Mohan Reddy et al. 1992; Mohan Reddy 1995; Reddy 1996; Mohan Reddy and Jacquot 1999; Durdu 2004, 2006; Lemos et al. 2009; Durdu 2010; Feng and Wang 2011; Shang et al. 2011; Xu et al. 2012; Breckpot et al. 2013; Soler et al. 2013a; Cen et al. 2017; Bonet et al. 2017; Lacasta et al. 2018). On the other hand, Malaterre (1998) uses an implicit Preissmann finite-difference scheme, with the advantage that the stability of the model does not depend on the discretization step size, and Liu et al. (1998) propose the use of this scheme in the development of a control strategy based on an inverse solution of the nonlinear SVE. The use of control-oriented models based on the Preissmann scheme has been reported in multiple studies (e.g., Pages et al. 1998; Malaterre and Khammash 2003; Figueiredo et al. 2013). Finally, Dulhoste et al. (2004) propose the use of an orthogonal collocation method to obtain a finite-dimensional model. The advantage of this numerical method relies on its less-computational effort with respect to other numerical methods in the solution of partial differential equations. However, when the main purpose is to obtain a control-oriented model, the orthogonal collocation method is not the best option, since the mathematical synthesis of the method is harder than the spatial discretization and the Preissmann scheme.

In the second subgroup, the continuous spatial structure is preserved. However, linearizations, transformations, and partial solutions of the linearized SVE are proposed. Hayami (1951) propose the linearization of the SVE with the intention of analyzing the flow in rivers. Later, Corriga et al. (1980) propose the Laplace transformation of the linearized SVE with the aim of obtaining analytical solutions that describe the behavior of the level and flow along the channels. Then, the analytical solutions are evaluated in the boundary conditions obtaining delayed transfer functions that describe the relationship between channel inflow and outflow. The modeling strategy proposed by Corriga et al. (1980) has been adopted by Reddy (1990a) and Qiao and Yang (2010), who perform a more detailed explanation of the linearization of the SVE. One disadvantage of this strategy is that the model parameters are based on mean values of variables in steady-state conditions (Schuurmans, 1997). Litrico and Fromion (2004a) show that the linearized Laplace transform of the SVE are spatial linear ordinary differential equations that are solved obtaining a transfer function matrix with y_{up} and y_{dn} as outputs, and Q_i and Q_{i+1} as inputs. This model is called the *integrator delay zero model* (IDZ), which has been contrasted with the frequency domain response and time response of linearized SVE numerically solved with a Preissmannn scheme showing a similar behavior (Litrico and Fromion, 2004b). Additionally, Litrico and Fromion (2004c) propose a systematic procedure to use the IDZ to obtain control-oriented models of OCIS. This modeling strategy shows more accurate behavior than other techniques in resonant systems (Clemmens et al., 2017), and recently, has been used for modeling, control, and estimation purposes (e.g., Horváth et al. 2014; Puig et al. 2015; Dalmas et al. 2017; Segovia et al. 2017, 2018b,a). Similar to the work developed by Litrico and Fromion (2004a), Ouarit et al. (2003) establish a transfer function matrix, where the flow is also an output of the system, and the inputs are related to the regulation structures position. The advantage of this model is that there are not assumptions of uniform regime along the channel, consequently, this model has been called as an *IDZ model in non-uniform regime* (Dalmas et al., 2017).

Finally, another reported way to simplify the SVE is to neglect their inertial terms. This strategy has been reported by Papageorgiou (1983) and Montero et al. (2013). In the modeling strategy reported by Papageorgiou (1983), a first-order delay differential equation that describes a relation between the downstream depth and upstream depth of a channel is obtained. This strategy is reported again by Papageorgiou and Messmer (1985). On the other hand, in the strategy reported by Montero et al. (2013), a more complex partial differential equation that needs to be solved using numerical methods is obtained. It must be highlighted that the simplified modeling strategy proposed by Papageorgiou (1983) could be useful for obtaining control-oriented models that include the nonlinear behavior of gates and weirs in submerged and free flows.

Given these models, it is identified that most of the simplified modeling strategies require operational information of the system. For instance, key parameters of the simplified models proposed by Hayami (1951), Corriga et al. (1980), and Litrico and Fromion (2004a), need information about mean flow velocity, which can change in the presence of strong disturbances like obstructions or even with level and/or flow changes. Moreover, in the cases of finite-difference schemes, models with high order are obtained. These aspects can be considered as drawbacks in control systems designs. Therefore, in order to avoid these issues, some researchers have contributed to the development of new approximated modeling strategies with practical assumptions.

3.2. Approximated Models

The approximated models such as the Muskingum model, the integrator delay model (ID), the gray-box models, and the black-box models, are models that have been developed from practical assumptions, using basic physical principles, observations, and empirical knowledge. Even though the approximated models do not have rigorous physical fundament, the reported works have shown that the approximated modeling strategies are an important alternative to obtain control-oriented models for OCIS. Therefore, a more detailed description of these strategies is given next.

The Muskingum model, proposed by McCarthy (1939) from observations of the Muskingum river data, is one of the most widely used models for flow routing analysis. The Muskingum model has a mass balance per channel and an storage-discharge equation, which are used to obtain a transfer function that relates the inflow with the outflow of a channel. This information is not useful when the objective is to control either the upstream or downstream channel depth. However, it is possible to assume a two-part channel division, where the first part is described by the Muskingum model, and the second part is a reservoir described by the continuity equation, obtaining a transfer function that relates the inflow and the downstream level (Horváth et al., 2014).

In his doctoral thesis, Schuurmans (1997) proposes the integrator delay model, which is inspired by the modeling strategy proposed by Corriga and includes the phenomenon known as *backwater profile*. The characteristic of this phenomenon is that, at the downstream end of the channel, there is an accumulation of water. In this model, the channel is assumed to be divided into two parts: the first part corresponds to a uniform flow, and the other (considered as the backwater), where the system is analyzed as a reservoir. In that form, the depth along the uniform part is a function of the flow, and the backwater part is modeled as a mass balance with an inflow delay. The main advantage of this strategy is the simplicity of the model. Therefore, in the literature, the integrator delay model is one of the most reported modeling strategy for OCIS, which has been used for control design in multiple studies (e.g. Wahlin 2004; Litrico and Fromion 2004c,a; Koenig et al. 2005; van Overloop et al. 2005; Litrico and Fromion 2006b; Litrico et al. 2007; van Overloop et al. 2008a; Litrico and Fromion 2009; van Overloop et al. 2010a; Horváth et al. 2014; Bolea et al. 2014c; Van Overloop et al. 2014; Horváth et al. 2015b,a; Zheng et al. 2019).

The use of measured data is another important option to obtain control-oriented models for OCIS. This strategy called identification can be used to obtain models without physical knowledge of the system (black-box models), or models that present a structure based on the physical knowledge of the system (gray-box models) (Horváth et al., 2014).

The black-box or experimental models can only be obtained with measurements from a real system, and the result does not describe the physical phenomena, (it only describes the relationship between the measurement input and output data (Roffel and Betlem, 2007)). For example, Begovich et al. (2007) use a matrix of second-order discrete transfer functions in the identification of four open-channels, where the validation results show a high correlation between the real system and the obtained model in a variation depth zone of 0.04m. The parametric identification method can be either batch or recursive. In the batch identification method, by an experimental procedure, a set of input and output data is acquired from the system and, with the use of an optimization algorithm, the parameters of the model are obtained. On the other hand, in the recursive method, the parameters of the system are obtained during the control process, and the obtained model could be used in tuning the controller in real-time. One important advantage of the recursive optimization is that this method is useful to deal with time-variant parameter systems (Rivas Perez et al., 2007) and nonlinearities (Diamantis et al., 2011). The structure selection is another important aspect in the identification process, which can be outup-error

(OE), autoregressive exogenous (ARX), autoregressive moving average with exogenous inputs (ARMAX), and Box–Jenkins, among others (Roffel and Betlem, 2007). The most common structure used in systems identification is the ARMAX structure, since it includes dynamics of the disturbances (Rivas Perez et al., 2007). However, Sepulveda (2007) presents a detailed methodology to obtain identification models using ARX structures in real channels. Another important technique used to obtain control-oriented models for OCIS is the step response identification, in which from a step stimulus at the input, a transfer function that describes a similar behavior is adjusted. In OCIS, the transfer function is usually a second-order delayed function (e.g., Feliu-Batlle et al. 2007, 2009a; Blesa et al. 2010; Feliu-Batlle et al. 2011; Bolea et al. 2014a) or a first-order delayed function (e.g., Romera et al. 2013; Bolea et al. 2014b). On the other hand, OCIS that are deep, short, smooth, and have low flows are expected to be dominated by resonance behavior. In these cases, the order of the resultant transfer function is higher because there are resonant characteristics that, in short channels, are more dominant (Van Overloop et al., 2014). Therefore, Van Overloop et al. (2014) propose the *integrator resonance model* composed of one integrator and one underdamped second-order transfer function. This model has the particularity of not having a time delay. The model is validated with a laboratory channel, which is controlled with predictive controllers designed from *integrator delay model*, *integrator delay model plus a first-order filter*, and the *integrator resonance model*. The system controlled with predictive controllers designed from *integrator resonance model* shows the best performance.

The use of data-driven modeling tools is also presented in the development of models that describe the dynamics of OCIS. Tavares et al. (2013) propose a comparison between models based on neural networks, fuzzy systems, and linear systems. The result shows that describing the behavior of OCIS, the neural networks are slightly better than the linear and fuzzy systems. Herrera et al. (2013) use pattern search methods in online identification of the time-varying delay of OCIS. This strategy, called *multi-model scheme*, uses a set of models with diverse and updated time delays, where a pattern search algorithm estimates the amount of the corresponding time delay. On the other hand, in the field of gray-box models, Weyer (2001) proposes a control-oriented model based on a simplified mass balance, assuming that the water volume in the channel is proportional to the water level and there is a time delay in the channel inflow. Therefore, the model proposed has a differential equation by channel that describes a mass balance, where the nonlinear flow relation of the regulation structures is incorporated. This modeling strategy has been used for control design, and leak detection in multiple works (e.g., Weyer 2002; Zhang and Weyer 2005; Li et al. 2005; Ooi and Weyer 2005; Mareels et al. 2005; Choy and Weyer 2006; Weyer 2006; Cantoni et al. 2007; Ooi and Weyer 2008b; Weyer and Bastin 2008; Weyer 2008; Ooi and Weyer 2008a, 2011; Bedjaoui and Weyer 2011). In OCIS, the reported gray-box models are nonlinear models, and these models are more accurate than the linear models representing the dynamics of OCIS (Weyer, 2001). Additionally, these models could be used to test the behavior of linear controllers in presence of nonlinearities associated with the regulation structures. However, in most of the cases, the gray-box models have been only used for systems with weir structures in free-flow. In these cases, the flow is only a function of the regulation structure upstream depth. Eurén and Weyer (2005) use gray-box models in a system with both undershoot and overshoot regulation structures. However, this work is developed in a single channel, without opportunities to analyze the configuration of the model when there are channel interactions.

4. Control

In OCIS, the principal objective is to deliver the appropriate amount of water to each user. In a well-operated system, the intake water must be equal to the water used or, in other words, the wastage of water should be reduced to a minimum (Weyer, 2008). Ideally, this is an easy task when there are no dynamics in the system. However, OCIS are complex systems with long delays, high channel interactions, intermittent demands, disturbances, and multiple inputs and outputs. Consequently, the control of OCIS can be analyzed using multiple approaches, which are complex to classify (Malaterre et al., 1998). However, these approaches, which have been classified in control architectures, control objectives, control-action variables, control configurations, and control strategies are presented next.

4.1. Control Architectures

The most common control architecture in OCIS is the centralized architecture, where the input and output variables of the system are declared as vectors, i.e., $Q_{out} = [Q_{out_i}, Q_{out_{i+1}}, ...]^\top$, $u = [u_i, u_{i+1}, ...]^\top$, $Q = [Q_i, Q_{i+1}, ...]^\top$, $y_{dn} = [y_{dn_i}, y_{dn_{i+1}}, ...]^\top$, $y_{up} = [y_{up_i}, y_{up_{i+1}}, ...]^\top$. Then, the multiple measurements that could be obtained from the system are used to compute the control-action variables (e.g., Begovich et al. 2007; Nasir et al. 2018; Aydin et al. 2017; Horváth et al. 2015b,a), and the control action are generated by a central controller (Malaterre, 1995). On the other hand, in a decentralized architecture (e.g., Gomez et al. 2002; van Overloop et al. 2005; Segovia et al. 2017; Weyer 2008), only local upstream or downstream information of a channel is used to compute the control strategy. Finally, in a distributed architecture, the control system computation uses local and adjacent information establishing cooperation among local controllers (Le-Duy-Lay et al., 2017).

In centralized architectures, it is possible to reach a better performance than in both decentralized and distributed architectures. However, a decentralized or distributed control system offers the possibility of keeping the system controlled (with a possible performance degradation) even if part of the information is lost. In addition, non-centralized architectures allow partial implementations in channels according to budget and relevance. Although OCIS are strongly coupled systems, in some cases for decentralized schemes, each channel is taken as an independent system and the control design only deals with the problem of controlling a particular channel. This kind of approach can lead to unacceptable performance or even instability of the whole system (Schuurmans, 1997). On the other hand, some authors propose to join the advantage of the centralized and decentralized architectures into a hierarchical control architecture. In the hierarchical control architecture, the performance of a system under decentralized schemes is enhanced with coordination of a centralized controller. In this architecture, the decentralized controllers keep the system controlled even if the communication is lost, and in order to enhance the overall performance and even to prevent risks, the centralized system modifies the targets of the decentralized systems (e.g. Zafra-Cabeza et al. 2011; Fele et al. 2014; Sadowska et al. 2015a; Farhadi and Khodabandehlou 2016). For the sake of simplicity, and the need of a centralized controller, in this review, the hierarchical control architecture is treated as a case of centralized control architecture.

4.2. Control Objectives

Usually, in OCIS, a constant depth is set at each channel, and with the position adjustment of the outlet structure, the discharges are regulated to each user (Cantoni et al., 2007). In decentralized and distributed control architectures, the use of the terms *upstream control* and *downstream control* is common. In the upstream control, a fixed level upstream of the cross regulation structure is maintained (e.g., Malaterre 2008; Rijo and Arranja 2010; Clemmens et al. 2017; Figueiredo et al. 2013), while in the downstream control, the level is maintained downstream of the cross regulation structure (e.g., Malaterre 2008). Additionally, the upstream and downstream control can be close, intermediate, or distant to the regulation structure. In the literature, there are no reports about the use of intermediate downstream and upstream control since this implies measuring the depth in an intermediate part of the channel and the hardware adequacy far from the cross structures is impractical. Distant upstream control is another infrequent alternative. For instance, Lemos and Sampaio (2015) establish that this configuration does not guarantee a water level along the channel. Additionally, Rato et al. (2007) compare the effectiveness of an adaptive controller implemented in an open-channel, first controlling the upstream level close to the regulation structure, and second testing the same strategy controlling the upstream level distant from the regulation structure. In the first configuration, the results of the adaptive strategy present an appropriate behavior, but in the second configuration, the adaptive strategy shows oscillations and undesirable performance. Regulate the upstream level close to the regulation structure is the most common control method in OCIS (Clemmens et al., 2017). This method requires a flow control at the intake of the system, where the intake flow is calculated in order to satisfy the users' demands. Therefore, excess in the intake flow will result in spills. In contrast, deficiencies in the intake flow, losses, or unforeseen demands will result in deficient flow at the system downstream.

In downstream control, each regulator delivers the amount of flow to maintain the level downstream of the cross structure. Therefore, this is known as a completely automatic method of controlling water levels (e.g., Wahlin and Zimbelman 2014). In the close downstream control case, the objective is to maintain a constant level at the upstream end of the channel, and in the distant case, the level is maintained at the downstream end of the channel. One advantage of controlling the level at the upstream end of the channel is that there is always a storage volume to supply rapidly unforeseen demands (Malaterre, 2008). From a control perspective, there are no reports about the advantages or drawbacks of the distant downstream controllers. However, it is necessary to mention that Malaterre (1995) points out that when the depth at the downstream end of a channel is controlled, there are not inconveniences with the slope of the channel, reducing construction costs.

Moreover, the controller can be multivariable and the controlled variables could be: i) the upstream depth (e.g., Rijo and Arranja 2010; Breckpot et al. 2013); ii) the downstream depth (e.g., Nasir et al. 2018; Aydin et al. 2017; Le-Duy-Lay et al. 2017; Horváth et al. 2015b,a); iii) the channel inflow or outflow (e.g., Puig et al. 2015; Litrico and Georges 1999); iv) the outlet flow; or v) a combination of depths and flows (e.g., Balogun et al. 1988; Breckpot et al. 2013).

Finally, the accomplishment of the control objectives can be measured by using key performance indicators. In the reported literature, the most used indicators are proposed by Clemmens et al. (1998), which are oriented to examine the amount of error in the water levels, and the excessive position variations that the regulation structures present. As it is shown by Clemmens et al. (1998), the desirable situation is to maintain a fixed level along the channel and, with the position adjustment of the regulation structure, deliver the appropriate amount of water to the users. Moreover,

Variable of interest	Key Performance Indicator
Error in water levels	$MAE = max\left(\frac{\lvert \mathbf{y_{dn_i}} - \mathbf{r_{dn_i}} \rvert}{r_{dn_i}}\right)$ $IAE = \frac{\frac{1}{N}\sum_{k=0}^{N-1} \lvert y_{dn_i}(k) - r_{dn_i} \rvert}{r_{dn_i}}$ $StE = max\left(\frac{\lvert \bar{\mathbf{y}}_{\mathbf{dn_i}} - \mathbf{r_{dn_i}} \rvert}{r_{dn_i}}\right)$
Gates and flow change	$IAQ = \sum_{k=0}^{N}\left(\left\lvert Q_i(k) - Q_i(k-1)\right\rvert\right) - \left\lvert Q_i(0) - Q_i(N)\right\rvert$ $IAW = \sum_{k=0}^{N}\left(\left\lvert u_i(k) - u_i(k-1)\right\rvert\right) - \left\lvert u_i(0) - u_i(N)\right\rvert$

Table 3
Key performance indicators for error in water levels and changes in flows and gates, where the level error at the downstream end of the channel is considered and $\mathbf{y_{dn_i}} = [y_{dn_i}(0)\ y_{dn_i}(1)\ \ldots\ y_{dn_i}(N-1)]^\top \in \mathbb{R}^N$ is the vector of the level measurements, r_{dn_i} is considered as a desired level, $\mathbf{r_{dn_i}} = [r_{dn_i}\ r_{dn_i}\ r_{dn_i}]^\top \in \mathbb{R}^N$ is considered as a desired level vector, and $\bar{\mathbf{y}}_{\mathbf{dn_i}}$ is the mean of $\mathbf{y_{dn_i}}$

because excessive gates and flows changes produce mechanical wear and water levels oscillations, to reduce excessive gates and flows changes is desired. The key performance indicators can be used as a measure of performance for controlled systems (e.g., Xu et al. 2012; Munir et al. 2012; Soler et al. 2013a; Bonet et al. 2017; Ke et al. 2018; Zheng et al. 2019), and as a design criteria in optimal controllers (e.g., Feliu-Batlle et al. 2011; Ke et al. 2018). A relation of the principal key performance indicators is presented in Table 3, where: i) the maximum absolute error (MAE) is the maximum normalized error between the desired and measured level; ii) the integral of the absolute error (IAE) accounts for the cumulative level error along a time period (T); iii) the steady-state error (StE) is the maximum absolute level error during a time period when the steady state has been reached; iv) the integral square error (ISE) also accounts for the cumulative level error and weights large deviations; v) the absolute gate movement (IAW) relates to positions changes of the regulation structures; and vi) the integrated absolute discharge change (IAQ) accounts for flow variations.

4.3. Control-Action Variables

Certain dynamics could be associated with the movement of the regulation structures and the necessary instrumentation. In controlled systems, most of these dynamics are modified with master-slave control configurations, which are shown in Fig. 5, where the most usual configurations are presented. In the first case, a position control is shown, where ZI is a position sensor and ZC is a position control that regulates the voltage for the servo-motor (Sepulveda, 2007). In the second case, a more elaborated control scheme is shown, where LI corresponds to the level indicators and FC is a flow control (Schuurmans, 1997). The inclusion of master-slave flow control is useful to divide the control problem into sub-problems, where the dynamical and non-linear relations that there are between

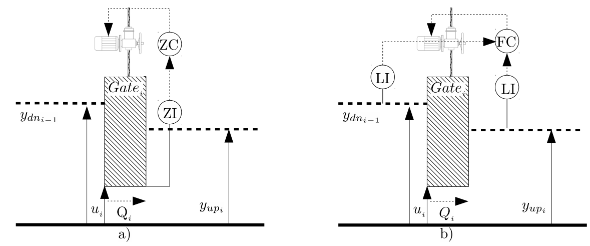

Fig. 5: Master-slave configuration examples: a) Aperture gate control. b) Flow control.

flow, regulation structure position, regulation structure mechanism, and water levels can be overcome. Therefore, assuming that the controlled structure has zero steady-state error, high damping factor and short time constant, the model of an open-channel irrigation system could be reduced to a linear model with time delays, where the system input is a flow instead of a regulation structure position.

4.4. Control Configurations

In OCIS control, choosing between feedback (FB) and feedforward (FF) control configurations or a combination of both ($FB + FF$) also is possible. In FB configuration, the channel inflow or outflow generally changes in order to decrease the error between the controlled variable and a desired level or flow. In FF configuration, the channel inflow or outflow changes according to previous information about demands. Each configuration has its advantages and drawbacks. With FB configuration (e.g., Breckpot et al. 2013; Rijo and Arranja 2010; Durdu 2010; Weyer 2008; Litrico and Fromion 2006a; Durdu 2006), the rejection of disturbances and uncertainties such as source-level variations, leaks, unexpected demands, meteorological fluctuations, and changes in parameters of the system can be reached. However, improper design of the controller could lead to oscillations or even instability. On the other hand, in FF configuration, OCIS have fewer fluctuations and faster response. However, with this configuration, the rejection of disturbances and uncertainties is unavailable (van Overloop et al., 2008b). Some research works take advantage of both configurations ($FB + FF$), obtaining faster responses and the possibility to reject disturbances and uncertainties (e.g., Gomez et al. 2002; Van Overloop et al. 2014; Sadowska et al. 2015a; Puig et al. 2015; Horváth et al. 2015a,b; Le-Duy-Lay et al. 2017; Aydin et al. 2017; Nasir et al. 2018).

4.5. Control Strategies

Finally, the control of OCIS could be seen as a problem of multiple inputs or multiple outputs, with or without disturbances, represented by linear or non-linear models. In this sense, multiple control strategies have been tested and reported in the literature. Next, a brief introduction to the most common strategies is presented and some examples are identified.

4.5.1. PID Control

Proportional-integral-derivative (PID) control is the most commonly used control algorithm in the industry, as well as in OCIS (Litrico et al., 2007). Several studies that use PID controllers to maintain a fixed level in the OCIS have been reported. For example, Burt et al. (1998) establish methods and strategies for tuning upstream PI controllers; Litrico and Georges (1999) compare the performance of a PID controller with a pole placement controller with Smith Predictor; Litrico et al. (2003) investigate the convenience between using a PI controller to maintain a fixed upstream level or a fixed downstream level; van Overloop et al. (2005) modify a PI controller with a first-order filter with the aim to reduce resonant oscillations that are induced from neighbor channels; Lozano et al. (2010) evaluate the performance between a downstream PI controller and a distant downstream PI controller; Figueiredo et al. (2013) test a PI downstream controller in a system with fourth channels; Bolea et al. (2014c), in a real system, assess the behavior of a PI controller designed from a Muskingum model and other from an integrator delay; recently, Arauz et al. (2020); Ke et al. (2020) present two PI tuning methods, that have been designed using the integrator delay modeling approach. It is important to realize that the control strategy proposed by Arauz et al. (2020) has been tested in specialized software (SOBEK), showing that optimally tuned PI controllers are successful for level regulation of OCIS. Other studies simply use the PID controllers to compare the performance of more sophisticated control strategies (e.g., Malaterre and Khammash 2003; Zheng et al. 2019). On the other hand, the design and structure of the PID controllers have been modified with the aim of overcoming uncertainties that are associated with the OCIS. These modifications can be split into two categories: one category is conformed by PID controllers designed in frequency domain considering the robustness of the controlled system (e.g., Litrico and Fromion 2006b; Feliu-Batlle et al. 2007, 2009a, 2011). Another one is conformed by the use of adaptive parameters that must adapt to the controlled system (e.g., Litrico et al. 2007; Bolea et al. 2014a).

4.5.2. LQR and LQG

One of the most popular strategies in the control of OCIS is based on the use of optimal controllers, where the objective is to find a control law that minimizes a quadratic cost function formulated from the representation of the system in state-space. This strategy is known as linear quadratic regulator (LQR), whose advantage is that the control law is a gain vector that weighs the states of the system, being this vector obtained by a systematic solution of the Riccati equation (Kirk, 2004). It has been shown that, in systems modeled by explicit and implicit finite-difference schemes, the use of LQR is popular because this strategy is practical for controlling systems with a large number of states (e.g., Balogun et al. 1988; Reddy 1990b; Mohan Reddy et al. 1992; Schuurmans 1997; Mohan Reddy and Jacquot 1999; Durdu 2006, 2004). In the same direction, the linear quadratic Gaussian (LQG) control, which corresponds to an LQR control with a Kalman filter as an estimator for the non-measurable states, becomes a popular alternative when the systems are modeled using explicit and implicit finite-difference schemes (e.g., Mohan Reddy 1995; Reddy 1996; Schuurmans 1997; Mohan Reddy and Jacquot 1999; Durdu 2006, 2010). Similarly, the LQR control strategy could be used in either decentralized or distributed control schemes. For example, Ke et al. (2018) analyze the behavior of optimally tuned single-input and single-output (SISO) PI controllers designed from control-oriented models obtained with the integrator delay approach. One drawback is that LQR are linear controllers designed to have a desired behavior in a region close to an operation point.

4.5.3. Model Predictive Control (MPC)

Essentially, MPC is a control strategy that has aroused the interest of researchers in control of OCIS (e.g., Begovich et al. 2007; Sepulveda 2007; van Overloop et al. 2008b; Lemos et al. 2009; Negenborn et al. 2009; van Overloop et al. 2010a,a; Cembrano et al. 2011; Xu et al. 2012; Breckpot et al. 2013; Figueiredo et al. 2013; Van Overloop et al. 2014; Horváth et al. 2014; Sadowska et al. 2015a; Puig et al. 2015; Horváth et al. 2015a,b; Cen et al. 2017; Segovia et al. 2017; Le-Duy-Lay et al. 2017; Aydin et al. 2017; Nasir et al. 2018; Zheng et al. 2019). This is due to the benefits that MPC offers in terms of optimality and prediction. Additionally, this kind of controller can be designed from any control-oriented model previously presented and can be used in centralized, distributed, and decentralized architectures. This control strategy is composed of four elements: i) a prediction model; ii) a set of constraints; iii) a cost function; and iv) an optimization algorithm. The mathematical model of the system must be synthesized in discrete-time, and can be expressed in state-space or transfer function representations. The prediction model is developed from a discrete-time model of the system and the current value of the state variables. The maximum and minimum values that limit the operation range of the controlled system are incorporated into the constraints set for the system inputs and state variables, and the cost function synthesizes the performance criteria with a linear or non-linear combination of the prediction model and the set of constraints. Finally, the optimization algorithm searches for the optimal control sequence over a prediction time horizon that minimizes the cost function

(Maciejowski, 2002). One drawback of the MPC is that the behavior of this strategy has a high dependency on the system model, and when there are disturbances not included in the model, the controller could show undesirable behaviors (Lemos et al., 2009; Horváth et al., 2015b). This problem can be overcome with the inclusion of adaptive strategies (Lemos et al., 2009), and the use of incremental states and incremental actions (Horváth et al., 2015b; Aydin et al., 2017).

4.5.4. Other Control Strategies

PID, LQR, and MPC are the most reported strategies in control of OCIS. However, control systems is a dynamic field, where multiple control strategies are continuously emerging, and some of these strategies have been tested in control of OCIS. For instance, when OCIS are seen as a multi-input multi-output problem or single-input single-output problem with uncertainties, the H_∞ control strategy is a convenient option since it produces a solution that can explicitly include robust performance in the design procedure, taking into account explicitly information or assumptions on the uncertainties. In this strategy, the objective is to find a proper control law that stabilizes the closed-loop system and minimizes the H_∞ norm of an augmented linear model that takes into account the uncertainties associated with disturbances and operational point changes (Litrico and Fromion, 2003, 2006a; Cantoni et al., 2007).

To the best of the authors knowledge, there are only two reported strategies where the SVE have been used directly as a control-design model: the first one, reported by Liu et al. (1995), is based on an explicit solution procedure of the SVE, which has been tested in a simulated OCIS with six channels showing high sensitivity to variations in physical dimensions of the channels and low sensitivity to variations in coefficients of the regulation structures; and the second one, reported by Dos Santos and Prieur (2008), where a non-linear control technique, which uses directly the SVE and is called a boundary control (BC), is established. The control strategy is tested in a simulated system and in a small prototype, concluding that the controlled system presents suitable results, even though the proposed control technique is unsystematic.

Machine learning is a field that has been growing constantly and has been broadly applied in the solution of complex problems. In the control of OCIS, Hernández and Merkley (2010a); Shahverdi and Monem (2015); Shahverdi et al. (2016, 2020) use software agents that interact with models of the OCIS in order to maximize a reward function that is related to the regulation structures adjustment and the levels of the system. This technique, known as reinforcement learning, has been implemented using specialized simulation software where the OCIS are numerically solved, then, the strategy finds the optimal operational solution for each regulation structure, and this solution is applied to the irrigation system (Hernández and Merkley, 2010a). The main advantage is that this control strategy does not need an explicit model of the system, for this is considered a model-free strategy (Shahverdi et al., 2016). The OCIS controlled using reinforcement learning have shown satisfactory performance. However, to the best of the authors' knowledge, no previous reports exist on the use of machine learning in the control of real OCIS.

Another interesting control technique that has been reported is the linear parameter-varying (LPV) control, where the OCIS are modeled as parametrized linear systems with parameters that change with the operation point. Bolea et al. (2014b) propose the description of the OCIS as an LPV system, and subsequently, establish a PID with a Smith predictor LPV controller in order to deal with the nonlinearities and variable delays that describe the OCIS (Bolea et al., 2014a). The LPV controller is implemented in a real system with successful results. Similarly, adaptive control strategies, where there is a need to recursively identify the parameters, have been explored (e.g. Diamantis et al. 2011; Herrera et al. 2013).

Finally, the small head loss automatic gates (French acronym: AVIS) and the high head loss automatic gates (French acronym: AVIO), which are hydro-mechanical downstream controllers (Wahlin and Zimbelman, 2014), can be included as another kind of control strategy for OCIS. The drawback of these regulation structures is that they are more complex to develop than conventional gates or weir structures. These regulation structures are developed in France and have been manufactured in other countries, often unsuccessfully (Wahlin and Zimbelman, 2014).

5. Discussion

As previously stated, modeling and control of OCIS are complex problems with several choices and constraints that should be taken into account. In OCIS, the most common and appropriate approaches could be developed around the following questions:

- What are the decision features to select a suitable control-oriented modeling strategy for OCIS?
- Which control approaches might be suitable to increase the efficiency of the OCIS?
- In the field of modeling and control of OCIS, which are the research gaps and challenges that must be addressed?

Next, some ideas that address these questions are discussed.

5.1. Selecting a Suitable Control-Oriented Modeling Strategy

Most of the control-oriented modeling strategies have been tested in the designing of controllers for real systems, showing useful results. For example, Sepulveda (2007), Lemos et al. (2009), Rabbani et al. (2009), Figueiredo et al. (2013), Van Overloop et al. (2014), and Horváth et al. (2014) have shown in real systems the results of the implementation of controllers designed from simplified modeling strategies. On the other hand, Rivas Perez et al. (2007), Litrico et al. (2007) Sepulveda (2007), Begovich et al. (2007), Feliu-Batlle et al. (2007), van Overloop et al. (2008a), Feliu-Batlle et al. (2009a), Feliu-Batlle et al. (2009b), van Overloop et al. (2010b), Feliu-Batlle et al. (2011), Tavares et al. (2013), Bolea et al. (2014a), Van Overloop et al. (2014), Horváth et al. (2014), Sadowska et al. (2015a), and Cescon and Weyer (2017) have shown in real systems the results of the implementation of controllers designed from approximated models. However, the availability of a real system to test the behavior of designed control approaches is often unusual. For this reason, in the reviewed literature, only 25% of the works have reported the implementation and analysis of control techniques in real systems. In other cases, the control tests are developed over the control-design model, showing the obtained results as validated data, even though in OCIS, usually, the control-design models are linear models that do not describe most of the hydraulic behavior of real OCIS. In order to perform more rigorous control tests, one alternative could be to test the designed controllers in systems modeled with the SVE. However, the comprehension, codification and stability analyses of implicit or explicit numerical algorithms that solve the SVE of OCIS could be seen as complex tasks.

A second alternative could be the use of specialized hydraulic software such as: i) the stormwater management model (SWMM) software, developed by the Environmental Protection Agency of the United States (Lewis, 2017), which is of free distribution and use but with limited control systems alternatives; ii) The river analysis system developed for the hydrologic engineering center of the U.S. Army Corps of Engineers (HEC-RAS) is a specialized hydraulic software useful for modeling rivers and open channels. The HEC-RAS also is of free distribution and use, and let the coupling with other softwares such as Matlab (e.g. Leon and Goodell (2016)) and Python (e.g. Dysarz (2018)). iii) the software for simulation and integration of control for canals (SIC), which has shown to be suitable for testing control strategies in OCIS (Van Overloop et al., 2014), and offers a wide number of control alternatives (in this case, this software needs a license to be used); and iv) the integrated software package for river, urban or rural management (SOBEK) developed by the institute for applied research Deltares, which solves the SVE of hydraulic systems and lets the online coupling with Matlab, opening the control alternatives to the multiple control strategies that in Matlab can be developed (this software also needs a license to be used).

A final alternative is the use of approximated control-oriented models capable of describing most of the hydraulic behavior of real OCIS, without the intrinsic accuracy of the SVE. One example is the *gray-box model* proposed by Weyer (2008), which includes a mass balance and the non-linear hydraulic description of the regulation structures. However, most of these models are focused on obtaining control-oriented models for OCIS with weir regulation structures in free-flow, where there is no interaction between adjacent channels. This aspect is highly relevant, because gates in submerged-flow, where the inflow and outflow are a function of the upstream and downstream depth of the structure, are the most common discharge structures in OCIS (U. S. Department of the Interior, 2001). Therefore, the development of new approximated modeling strategies that describe the behavior of OCIS with different types of regulation structures is a challenge that needs to be further addressed.

5.2. Selecting a Suitable Control Approach

Along of the review, multiple control approaches have been outlined. Therefore, it is developed a classification of the available and most common OCIS control approaches that have been reported in the literature. First, in Fig. 6 a proposed classification of the available control approaches for OCIS is shown. In this classification, the sets of OCIS control alternatives are highlighted. For example, a control approach could be developed using the following choices: i) as a control architecture, a centralized control architecture; ii) as a control objective, maintains a constant depth at the downstream end of the channels; iii) as a control-action variable, the regulation structures position, which demands the inclusion of master-slave position controllers; iv) as a control configuration, a $\boldsymbol{FB}$ configuration; and v) as a control strategy, an MPC controller. On the other hand, from Fig. 6, it is also highlighted that a conventional PID control strategy is not available as centralized control architecture, and that MPC, LQR, and the other reported control strategies can be used in centralized, decentralized, and distributed control architectures. Additionally, in this classification (Fig. 6), the use of a pure $\boldsymbol{FF}$ configuration has been discarded because this control configuration is no more than an open-loop operation of the system, and do not offer alternatives to reject disturbance or model uncertainties. Moreover, in Fig. 6, it is highlighted the kind of master-slave control implementation that needs to be developed for each control-action variable. The proposed classification (Fig. 6) is an interesting starting point in the identification of possible control approaches for OCIS. However, if this classifi-

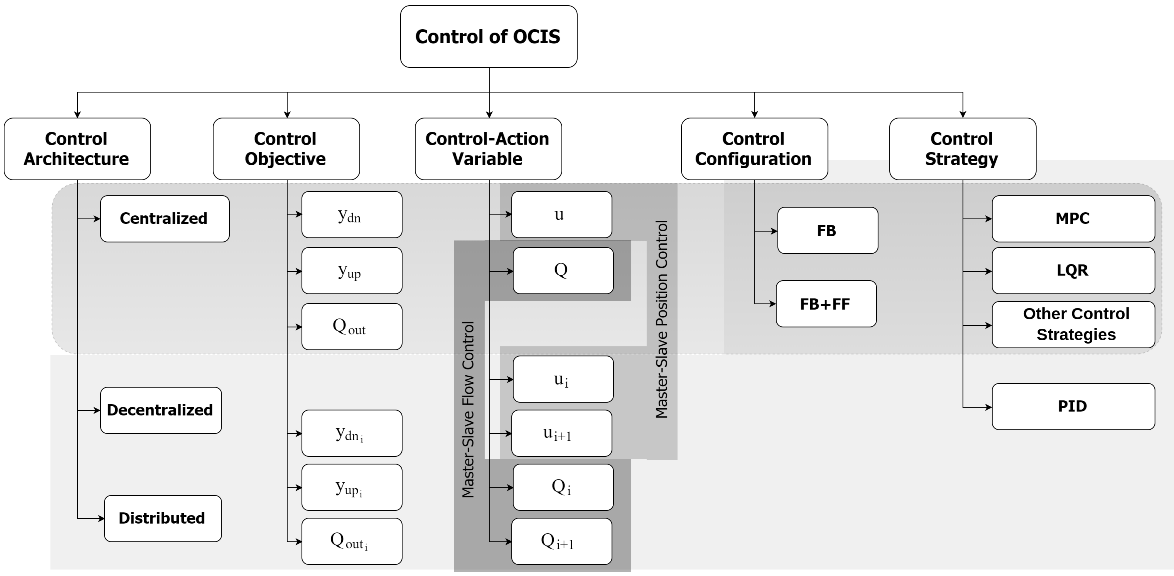

Fig. 6: Proposed classification of control approaches for OCIS.

cation is complemented with the classification for possible control-oriented modeling alternatives, presented in Fig. 4, A high number of combinations can be obtained.

In Table 4, it is presented a categorization of the available modeling and control approaches reported in the literature during the last years, where the main OCIS control choices are identified. In this table, the main aspects such as the control objective, the control-action variable, and the control-oriented model are included.

From Table 4, one of the most important aspects that can be highlighted is that, in OCIS, the most common control objective is to maintain a constant amount of water in each channel. Usually, this objective is reached using, as the controlled variable, the upstream depth or the downstream depth at the end of the channels. On the other hand, some few works explore the problem of controlling the flow that leaves the channels. One reason for this trend might be that if the controlled variable is the channel level, the OCIS can be described with a linear model, which is valid in a small region around the operation point of the system. Therefore, the controller can be designed in order to maintain the level of the channel into this region. On the other hand, if the controller only regulates the outflow, the channel level could be even at a point that does not guarantee the flow generation, or at a point that can generate overflows. However, most of the reported works that regulate outflows do not incorporate the feedback of the channel level.

Additionally, Table 4 also points out that the level regulation at the downstream end of a channel is more common than level regulation at the upstream end. This fact is well-accepted since controlling the level at the downstream end of the channel is easiest to prevent overflows due to water accumulation at the downstream end of the channel. Moreover, in Table 4 it is shown that, in order to maintain a constant level at the downstream end of the channel, using as a control-action variable the position of the regulation structure, most authors prefer as control-oriented model the use of finite differences, black-box models, and gray-box models. On the other hand, in the case of maintaining the constant level at the downstream end of the channel, using as a control-action variable the channel inflow, the ID model is the preferred control-oriented modeling strategy. As can be seen, the information in this table can be useful in the development and implementation of control strategies for OCIS, since, this table can be used to identify the most common OCIS control approaches and the sources where these approaches are reported.

In order to discuss about the reported control strategies, in Table 5, a chronological compilation of the reported control strategies for OCIS is presented. From this table, it can be highlighted that in OCIS, the most reported control strategies are PID and MPC. On the other hand, Malaterre (1995) shows that between 1980-1995, the LQR control strategy has been one of the most reported strategies for control of OCIS. However, it is shown that between 2007-2019, the interest in the research around using LQR for control of OCIS has been low. Similarly, Table 5 shows that there is a low interest in the exploration of other control strategies applied to OCIS. Another aspect to be highlighted is that the study around PID strategies for OCIS has been decreasing, and contrarily, the interest around MPC strategies has been growing. This increasing interest can be associated with the versatility that in the field of OCIS the MPC strategies offer, i.e., in Fig. 6 it is shown that the MPC strategy can be designed for the

Table 4
Reported works in control of OCIS, which have been classified according to the control-objective reported, the control-action variable used, and the control-oriented model selected.

Controlled Variable	*Control-Action Variable*	*Control-Oriented Model*	*Source*
y_{dn} y_{dn_i} $[y_{dn_i}\ y_{dn_{i+1}} \cdots]^T$	u_i u_{i+1} $[u_i\ u_{i+1} \cdots]^T$	Finite Differences	Lemos et al. 2009, Feng and Wang 2011, Shang et al. 2011, Soler et al. 2013a, Breckpot et al. 2013, Soler et al. 2013b, Bonet et al. 2017, Cen et al. 2017
		ID	Ke et al. 2018
		black-box Model	Litrico et al. 2007, Begovich et al. 2007, Feliu-Batlle et al. 2007, Feliu-Batlle et al. 2009a, Feliu-Batlle et al. 2009b, Lozano et al. 2010, Feliu-Batlle et al. 2011, Munir et al. 2012
		gray-Box Model	Cantoni et al. 2007, Domingues et al. 2011, Herrera et al. 2013, Bolea et al. 2014b, Sadowska et al. 2015a, (Horváth et al., 2015a)
	Q_i Q_{i+1} $[Q_i\ Q_{i+1} \cdots]^T$	Finite Differences	Xu et al. 2012, Figueiredo et al. 2013, Wagenpfeil et al. 2013, Zeng et al. 2020
		SVE Transformations (IDZ, Hayami model)	Goudiaby et al. 2013, Van Overloop et al. 2014, Horváth et al. 2014, Janon et al. 2016, Segovia et al. 2017, Segovia et al. 2019
		Muskingum	Bolea et al. 2014c, Horváth et al. 2014
		ID	Negenborn et al. 2009, van Overloop et al. 2010a, Bolea et al. 2014c, Van Overloop et al. 2014, Horváth et al. 2014, Nasir et al. 2018, Zheng et al. 2019, Hashemy Shahdany et al. 2019, Arauz et al. 2020, Ke et al. 2020
		gray-Box Model	Van Overloop et al. 2014, Horváth et al. 2015a, Horváth et al. 2015b, Aydin et al. 2017, Le-Duy-Lay et al. 2017, Tian et al. 2019
y_{up} y_{up_i} $[y_{up_i}\ y_{up_{i+1}} \cdots]^T$	u_i u_{i+1} $[u_i\ u_{i+1} \cdots]^T$	SVE	Dos Santos and Prieur 2008
		Finite Differences	Durdu 2010, Feng and Wang 2011, Breckpot et al. 2013, Cen et al. 2017, Lacasta et al. 2018
		Black-Box Model	Hernández and Merkley 2010b, Hernández and Merkley 2010a
	Q_i Q_{i+1} $[Q_i\ Q_{i+1} \cdots]^T$	SVE Transformations (IDZ, Hayami model)	Segovia et al. 2017, Clemmens et al. 2017
		Black-Box Model	Tavares et al. 2013
		gray-Box Model	Tian et al. 2019
Q_{i+1}	Q_i	SVE Transformations (IDZ, Hayami model)	Rabbani et al. 2009, Rabbani et al. 2010, Puig et al. 2015
		Black-Box Model	Diamantis et al. 2011,
		gray-Box Model	Bolea et al. 2014a

multiple control approaches presented in OCIS, let the inclusion of the schedule of the demands (e.g., Zheng et al. 2019), and offers the alternative of include multiple objectives into the control problem (e.g., Segovia et al. 2019).

Moreover, in order to quantify the collected information, in Fig. 7, bar charts that show the relation of modeling and control options that have been reported in the literature are presented. From this figure, it can be inferred that: i) due to the simplicity of the approximated models, most of the researchers (60%) use these modeling strategies; ii) close to the 90% of the reported works are focused on maintaining a constant depth in the OCIS, and usually (66%) this objective is reached by a control system that regulates the level at the downstream end of the channels; iii) in the literature, it is reported so far a similar interest around studying centralized and non-centralized control architectures, and despite that the OCIS are strongly coupled systems and the distributed architectures lead to partial implementation of controllers overcoming the problems that decentralized architectures presents, distributed control architectures appear as the less popular architecture in OCIS control research; iv) there is a slight preference in the use of the flow than the use of the structure position as control-action variable; v) only 30% of the reported works take the advantage of using $\boldsymbol{FB} + \boldsymbol{FF}$ configurations, which can be used to mitigate the delays and strong perturbations due to programmed outlet flows (Malaterre, 2008); and finally, vi) in OCIS, the MPC strategy emerges as the most studied control strategy.

Finally, it has been mentioned that the OCIS are usually manually controlled by operators, which can not take immediate action in order to mitigate the effects of disturbances. Therefore, even the implementation of the most simple and traditional control approaches can lead to increasing the OCIS efficiency. However, the research in control of OCIS must be conducted towards new control approaches that increase the efficiency of these systems, which means control approaches that increase the relation between used and taken water. However, in this review, it is highlighted that most of the reported research is focused on the control objective of maintaining fixed levels or volumes into the channels, and there are not reports that incorporate sources of losses like overflows, leaks, and evaporation into the control problem. Specifically, losses due to leaks halve the efficiency of the OCIS (Swamee

Table 5
Chronological compilation of reported control strategies for OCIS.

	PID	**MPC**	**LQR**	**Other Control Strategies**
2007	Litrico et al. 2007, Feliu-Batlle et al. 2007	Begovich et al. 2007		Cantoni et al. 2007
2008		van Overloop et al. 2008b		Dos Santos and Prieur 2008
2009	Lemos et al. 2009, Feliu-Batlle et al. 2009a, Feliu-Batlle et al. 2009b	Lemos et al. 2009, Negenborn et al. 2009		
2010	Lozano et al. 2010, Rijo and Arranja 2010	van Overloop et al. 2010a	van Overloop et al. 2010a, Durdu 2010	Hernández and Merkley 2010a, Hernández and Merkley 2010b, Blesa et al. 2010
2011	Domingues et al. 2011 , Feliu-Batlle et al. 2011, Feng and Wang 2011, Shang et al. 2011		Feng and Wang 2011	Diamantis et al. 2011
2012	Munir et al. 2012	Xu et al. 2012		Munir et al. 2012
2013	Herrera et al. 2013	Soler et al. 2013a, Breckpot et al. 2013, Soler et al. 2013b, Figueiredo et al. 2013, Wagenpfeil et al. 2013		Goudiaby et al. 2013
2014	Bolea et al. 2014c	Van Overloop et al. 2014, Horváth et al. 2014		Bolea et al. 2014a
2015	Sadowska et al. 2015a	Puig et al. 2015, Horváth et al. 2015a, Horváth et al. 2015b	Sadowska et al. 2015a	
2016				
2017	Clemmens et al. 2017	Segovia et al. 2017, Bonet et al. 2017, Aydin et al. 2017, Cen et al. 2017, Le-Duy-Lay et al. 2017		
2018		Nasir et al. 2018	Ke et al. 2018	Lacasta et al. 2018
2019	Zheng et al. 2019	Zheng et al. 2019	Zheng et al. 2019, Tian et al. 2019, Segovia et al. 2019	Liao et al. 2019
2020	Ke et al. 2020			Shahverdi et al. 2020, Zeng et al. 2020

et al., 2002). This problem has been analyzed from the structural construction of the channels (Swamee et al., 2002), but the specific challenge of design control algorithms for transporting water, minimizing losses due to leaks is a problem that has not been properly addressed so far.

5.3. Remaining Gaps

At this point, it has been identified that the development of suitable control-oriented modeling strategies and new control approaches that increase the efficiency of the OCIS is an open problem that must be addressed. However, this is not the unique research gap that in modeling and control of OCIS remains uncover. Therefore, some future directions from previous literature reviews in control of OCIS, and other identified gaps are listed next.

- In controlled systems, the flow through the regulation gate structures can change abruptly when the gate aperture changes close to the water surface, causing undamped oscillations in the channels levels. This problem is accentuated in channels that are short, flat, and deep (Van Overloop et al., 2014). This problem was first identified by Schuurmans (1997). Then, Litrico and Fromion (2004b) analyzed the problem in the frequency domain, and Van Overloop et al. (2014) developed and evaluated modeling and control strategies for channels sensible to oscillatory effects. However, more works and validation of multiple control and estimation strategies for oscillatory OCIS are needed.
- Since the dynamics of the OCIS are non-linear, the exploration of non-linear controllers in OCIS is recommended (Schuurmans, 1997). However,

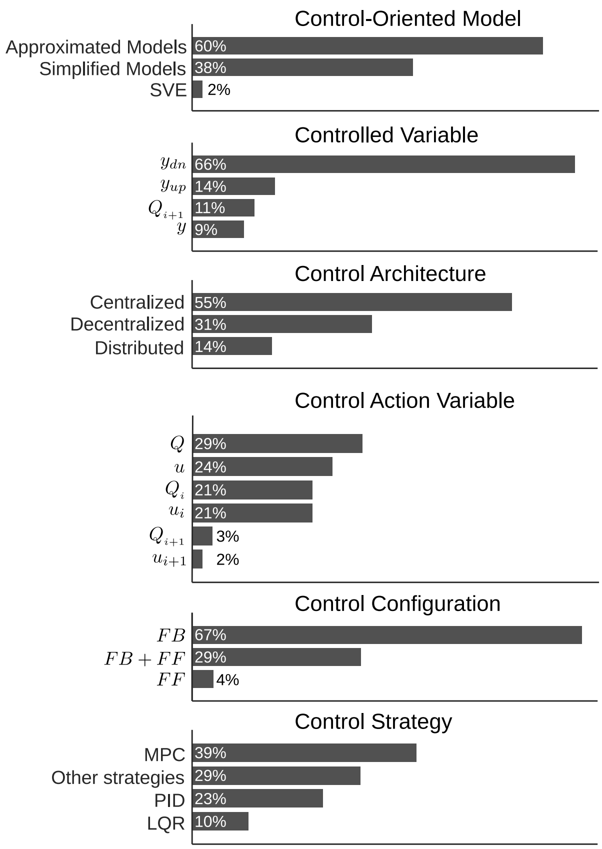

Fig. 7: Quantification of the modeling and control options reported in the literature.

there are few reports around non-linear control techniques for OCIS.

- In order to increase the efficiency in the use of water for agricultural systems, the integration of control of OCIS with crop behavior is an important challenge that must be addressed (Lamnabhi-Lagarrigue et al., 2017). This challenge has been explored by Hassani et al. (2019), with the development of an economic-operational framework used in a most economically efficient allocation of water, showing that this kind of development would improve the management of agricultural systems, improving economic, social, and environmental indicators under drought scenarios. However, the development of models and control strategies that explicitly account for static and dynamic interactions between water conveyance and crop behavior is a complex task that remains pending. In this direction, the exploration of cropping systems models such as WOFOST (de Wit et al., 2019), and LINTUL3 (Shibu et al., 2010) is recommended.
- The identification of unknown inputs such as leaks, sensor attacks, and failures in sensors and actuators has been studied in few works (e.g., Weyer and Bastin 2008, Bedjaoui and Weyer 2011, Amin et al. 2013b, Amin et al. 2013a, Segovia et al. 2018a). Additionally, robbery is one of the most important problems in OCIS. This problem is well analyzed in (Canute, 1971). However, the development of unknown input estimation strategies able to distinguish between the dynamical effect of a robbery episode or a leak is a topic that has not been fully solved.
- In OCIS, some operation conditions promote the sedimentation and growth of algae and bryophytes (Wahlin and Zimbelman, 2014), obstructing the channels. Therefore, in these systems, the maintenance operations must be frequent. However, to the best of the authors' knowledge, only the work developed by Fovet et al. (2013) has been reported around the use of control strategies to mitigate the algae grown in OCIS.
- In most cases the OCIS are manually controlled. This fact is basically associated to cost efficiency and security reasons. In this operation mode, the operator only uses local information from the point where the actuated gate is located. Therefore, the behavior of the controlled system is generally far from an optimal operation condition (van Overloop et al., 2015). This problem has been addressed by Maestre et al. (2014); Sadowska et al. (2015b); van Overloop et al. (2015) with the inclusion of human agents in the sensing and actuation of model predictive controllers. This is an interesting idea that has shown desired results in simulated systems. However, there are few works around this problem and, to the best of the authors' knowledge, there are no reports of the implementation of this control strategy in real systems.
- The development of control algorithms that include uncertainty effects appears as an interesting field that could increase the performance of the OCIS. The OCIS are continuously exposed to uncertain demands and meteorological effects. When the OCIS work on-demand mode, the outlet flows are seen as unknown disturbances that should be compensated by using a control strategy. However, Reddy (1996); Mohan Reddy and Jacquot (1999); Nasir et al. (2018) claim that with the use of historical outlet flows data and/or climatic conditions, it may be possible to describe these disturbances as uniform random variables, where the predicted average is equal to the outlet flow and there is a significant disturbance component with statistical information, which can be included in the control strategy. This is a promising control strategy. However, there are no descriptions about the algorithms that use these climatic predictions, and/or historical outlet flows data, in the prediction of the users' demands. On

the other hand, due to recent advances in meteorological effects prediction, the control of systems under meteorological effects is a challenging problem that is receiving more attention (Maestre et al., 2012). For example, Raso et al. (2013); Maestre et al. (2012); Raso et al. (2014); Ficchì et al. (2016) report the use of ensemble forecasting in the design of tree-based model predictive controllers for drainage water systems and reservoirs. In this control approach, the forecast uncertainty is used to set up a multistage stochastic problem, with the objective of finding multiple optimal strategies according to multiple forecast possibilities, showing that this control approach enhances the adaptivity to forecast uncertainty, improving the operational performance.

- In OCIS, both water quantity and quality criteria must be addressed. For example, salinity is a common problem in irrigated coastal areas (e.g., Aydın et al. 2019). However, the development of control systems that integrate water quantity and quality is scarce. This problem is broadly addressed by Xu (2013), where two simplified modeling strategies that relate quality and quantity are proposed, and the implementation of MPC controllers is evaluated, showing that both, quality and quantity can be controlled. However, real implementations and more studies around real-time quality measurement and consideration of uncertainties remain pending.
- Most of the rivers, lakes, and wetlands are supported by groundwater. Almost all the consumed freshwater is either groundwater or has been groundwater (Darnault, 2008). Therefore, this is a resource that must be protected, and its contamination and overexploitation must be avoided. However, as it is reported by Zhang et al. (2018), due to agricultural activities, nitrogen pollution of groundwater is growing. On the one hand, the OCIS are a direct recharge source for phreatic water. Therefore, the incorporation of measurement and control strategies that avoid groundwater contamination is an important task that must be addressed. On the other hand, as it is shown by Hashemy Shahdany et al. (2018), in many irrigation districts, groundwater is overexploited due to poor operational performance of the irrigation systems, and the groundwater consumption can be drastically reduced with the incorporation of suitable control strategies. Therefore, the development and implementation of control strategies that reduce groundwater consumption must be promoted.
- The SVE offers a fundamental and generalized description of the OCIS. However, due to the SVE complexity, its direct use for control systems design has been avoided. However, the OCIS are slow systems, and the current technology, as well as current model-based control algorithms (e.g., non-linear model predictive control), appears as an implementable strategy that could offer new objectives such as loss minimization.

6. Case study

The objective of this case study is to show a straightforward example for readers that are exploring practical aspects of the modeling and control of OCIS. Note that in order to ease the readability, most of the survey has been written in a descriptive form. Therefore, as an aggregated value, this case study has been introduced to show a contextualized description of the most popular modeling strategy (ID), and the most common control techniques that have been reported in the OCIS field (PID, LQR, and MPC). Moreover, in the case study, there are examples of centralized and distributed architectures, and feedback and feedback+feedforward configurations, as well as, examples about control-action variable and control objective. A case study with three channels is proposed, where the control objective is to maintain a constant depth at the downstream end of the channels, overcoming disturbances and outlet flows. The three channels are modeled using the ID control-oriented modeling strategy, and at the end of each channel, a permanent outflow is assumed to be regulated with an undershoot gate. Therefore, the outlet flow of the channel i is given by $\eta_i\sqrt{y_{dn_i}}$, where η_i is a constant. The model of the proposed case study is given by

$$\begin{aligned} A_1\dot{y}_{dn_1} &= -\eta_1\sqrt{y_{dn_1}} + Q_1(t-\tau_1) - Q_2 - Q_{out_1} \\ A_2\dot{y}_{dn_2} &= -\eta_2\sqrt{y_{dn_2}} + Q_2(t-\tau_2) - Q_3 - Q_{out_2} \\ A_3\dot{y}_{dn_3} &= -\eta_3\sqrt{y_{dn_3}} + Q_3(t-\tau_3) - Q_{out_3}, \end{aligned} \tag{2}$$

where $A_1 = 1000\text{m}^2$, $A_2 = 2000\text{m}^2$, $A_3 = 1000\text{m}^2$, $\tau_1 = 200\text{s}$, $\tau_2 = 300\text{s}$, $\tau_3 = 200\text{s}$. The η parameters are given by $\eta_1 = \sqrt{2}$, $\eta_2 = \sqrt{1.5}$, and $\eta_3 = 1$. In the case study, the three most common control strategies are tested (PID, MPC, and LQR). Consequently, in order to obtain a design model, the proposed system is linearized at an equilibrium point given by

$$0 = -\eta_i\sqrt{\bar{y}_{dn_i}} + \bar{Q}_i(t-\tau_i) - \bar{Q}_i - \bar{Q}_{out_i}, \tag{3}$$

where $\bar{y}_{dn_1} = 2\text{m}$, $\bar{y}_{dn_2} = 1.5\text{m}$, $\bar{y}_{dn_3} = 1\text{m}$, $\bar{Q}_1 = \bar{Q}_1(t-\tau_1) = 4.5\text{m}^3/\text{s}$, $\bar{Q}_2 = \bar{Q}_2(t-\tau_2) = 2.5\text{m}^3/\text{s}$, $\bar{Q}_3 = \bar{Q}_3(t-\tau_3) = 1\text{m}^3/\text{s}$, $\bar{Q}_{out_i} = 0\text{m}^3/\text{s}$. Hence, the following linearized model is obtained:

$$\begin{aligned} A_1\delta\dot{y}_{dn_1} &= -\frac{1}{2}\delta y_{dn_1} + \delta Q_1(t-\tau_1) - \delta Q_2 - \delta Q_{out_1} \\ A_2\delta\dot{y}_{dn_2} &= -\frac{1}{2}\delta y_{dn_2} + \delta Q_2(t-\tau_2) - \delta Q_3 - \delta Q_{out_2} \\ A_3\delta\dot{y}_{dn_3} &= -\frac{1}{2}\delta y_{dn_3} + \delta Q_3(t-\tau_3) - \delta Q_{out_3}, \end{aligned} \tag{4}$$

where $\delta y_{dn_i}(t)$, $\delta Q_i(t)$, and $\delta Q_{out_i}(t)$ are levels and flow variations around the equilibrium point. The linearized system describes a highest bandwidth given by $\omega_b = 1/2000$ rad/s. Therefore, following the recommendations presented by Litrico and Fromion (2009), the linear system is discretized with 100s sampling time (τ_s), obtaining the following linear discrete-time system:

$$\begin{aligned} \delta y_{dn_1}(k+1) =& a_{11}\delta y_{dn_1}(k) + a_{12}\delta Q_1(k-2) \\ &+ b_{12}\delta Q_2(k) + b_{d_{11}}\delta Q_{out_1}(k) \\ \delta y_{dn_2}(k+1) =& a_{44}\delta y_{dn_2}(k) + a_{45}\delta Q_2(k-3) \\ &+ b_{43}\delta Q_3(k) + b_{d_{42}}\delta Q_{out_2}(k) \\ \delta y_{dn_3}(k+1) =& a_{88}\delta y_{dn_3}(k) + a_{89}\delta Q_3(k-2) \\ &+ b_{d_{83}}\delta Q_{out_3}(k), \end{aligned} \tag{5}$$

where $\delta y_{dn_i}(k)$, $\delta Q_i(k)$, and $\delta Q_{out_i}(k)$ are the levels and flow variations at time instant k. Moreover, $a_{11} = \left(1 - \frac{\tau_s}{2A_1}\right)$; $a_{12} = \frac{\tau_s}{A_1}$;$b_{12} = -\frac{\tau_s}{A_1}$; $b_{d_{11}} = -\frac{\tau_s}{A_1}$; $a_{44} = \left(1 - \frac{\tau_s}{2A_2}\right)$; $a_{45} = \frac{\tau_s}{A_2}$;$b_{43} = -\frac{\tau_s}{A_2}$; $b_{d_{42}} = -\frac{\tau_s}{A_2}$; $a_{88} = \left(1 - \frac{\tau_s}{2A_3}\right)$; $a_{89} = \frac{\tau_s}{A_3}$; and $b_{d_{83}} = -\frac{\tau_s}{A_3}$.

LQR Design: With the objective to obtain a classical state-space realization of the linearized discrete-time system (5), the delays are transformed into states. In this direction, the proposed change of variables is shown in Fig. 8, where $x_1(k) = \delta y_{dn_1}(k)$; $x_2(k) = \delta Q_1(k-2)$; $x_3(k) = \delta Q_1(k-1)$; $x_4(k) = \delta y_{dn_2}(k)$; $x_5(k) = \delta Q_2(k-3)$; $x_6(k) = \delta Q_2(k-2)$; $x_7(k) = \delta Q_2(k-1)$; $x_8(k) = \delta y_{dn_3}(k)$; $x_9(k) = \delta Q_3(k-2)$; $x_{10}(k) = \delta Q_3(k-1)$; and z^{-1} is the representation of a discrete time delay. With this change of variables, the discrete linear system can be described as

$$\begin{aligned} x_1(k+1) =& a_{11}x_1(k) + a_{12}x_2(k) + b_{12}\delta Q_2(k) + b_{d_{11}}\delta Q_{out_1}(k) \\ x_2(k+1) =& x_3(k) \\ x_3(k+1) =& \delta Q_1(k) \\ x_4(k+1) =& a_{44}x_4(k) + a_{45}x_5(k) + b_{43}\delta Q_3(k) + b_{d_{42}}\delta Q_{out_2}(k) \\ x_5(k+1) =& x_6(k) \\ x_6(k+1) =& x_7(k) \\ x_7(k+1) =& \delta Q_2(k) \\ x_8(k+1) =& a_{88}x_8(k) + a_{89}x_9(k) + b_{d_{83}}\delta Q_{out_3}(k) \\ x_9(k+1) =& x_{10}(k) \\ x_{10}(k+1) =& \delta Q_3(k). \end{aligned} \tag{6}$$

Therefore, the discrete linear system can be synthesized using a classical state-space realization of the form $x(k+1) = Ax(k) + B\delta Q(k) + B_d\delta Q_{out}(k)$; and $y(k) = Cx(k)$, where $x(k) \in \mathbb{R}^{10}$ is the state vector; $\delta Q(k) \in \mathbb{R}^3$ the input vector; $\delta Q_{out}(k) \in \mathbb{R}^3$ the disturbance vector; $A \in \mathbb{R}^{10\times10}$ the state matrix; $B \in \mathbb{R}^{10\times3}$ the input matrix; $B_d \in \mathbb{R}^{10\times3}$ the disturbances matrix; and $C \in \mathbb{R}^{3\times10}$ the output matrix such that $y(k) = [x_1(k)\ x_4(k)\ x_8(k)]^\top$.

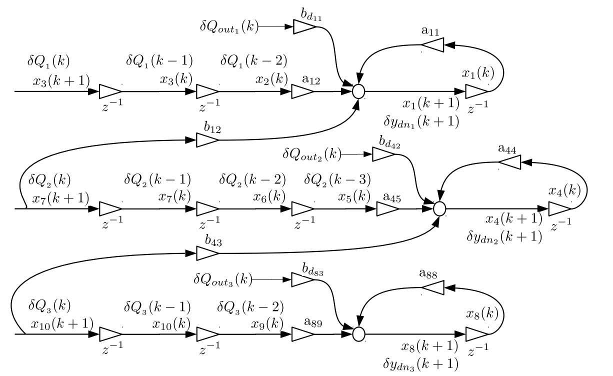

Fig. 8: Graphical description of the delays transformation into states, where $a_{i,j}$ is a constant at the i,j position of the state matrix, $b_{i,j}$ is a constant at the i,j position of the input matrix, and $b_{d_{i,j}}$ is a constant at the i,j position of the disturbances matrix

Figure 9 shows the proposed structure of a centralized LQR control for OCIS. Note that as it is shown in the change of variables, z^- indicates the states that can be obtained from time delays of the flow variations, and the integral part is included with the objective of having null steady-state error. Therefore, the controller is designed using an augmented system of the form $x_A(k+1) = A_Ax_A(k) + B_A\delta Q(k)$; and $y_A(k) = C_Ax_A(k)$, where $x_A(k) \in \mathbb{R}^{13}$ is the augmented state vector; $A_A \in \mathbb{R}^{13\times13}$ the augmented state matrix; $B_A \in \mathbb{R}^{13\times3}$ the augmented input matrix; and $C_A \in \mathbb{R}^{3\times13}$ the augmented output matrix. In specific,

$$A_A = \begin{bmatrix} \mathbf{I} & C \\ \mathbf{0} & A \end{bmatrix};\ B_A = \begin{bmatrix} \mathbf{0} \\ B \end{bmatrix};\ C_A = \begin{bmatrix} \mathbf{0} & C, \end{bmatrix}$$

where $\mathbf{I}$ and $\mathbf{0}$ are identity and zero matrices with suitable dimensions, respectively.

In Fig. 9, it is observed that the control law is given by $Q(k) = \bar{Q} + \delta Q$. This control law does not include information about the outlet flows, hence the controlled system has an FB configuration. Moreover, $K \in \mathbb{R}^{3\times13}$ is the control matrix. In order to obtain K, in the LQR controllers, the optimization problem to be solved is to maintain the state vector close to the origin without an excessive expenditure of control effort (Kirk, 2004). Then, the objective function to be minimized is given by

$$J = \sum_{k=0}^{\infty} \left({x_A}^\top(k)\mathcal{Q}x_A + \delta Q^\top(k)\mathcal{R}\delta Q(k) \right), \tag{7}$$

where $\mathcal{Q}$, $\mathcal{R}$ are diagonal weighting matrices that are used as tuning parameters that penalize the state and control variables. This test has been developed with diagonal values of 100 and 1 for $\mathcal{Q}$ and $\mathcal{R}$ respectively. The optimal regulation law is a linear combination of the system states of the form $\delta Q(k) = -Kx_A(k)$, and the matrix K is obtained through the solution of the Riccati equation (Kirk, 2004).

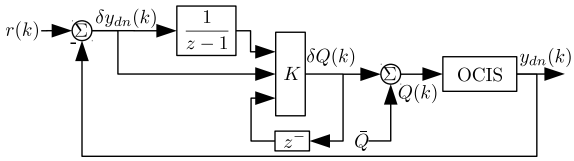

Fig. 9: Proposed structure of an LQR control for OCIS.

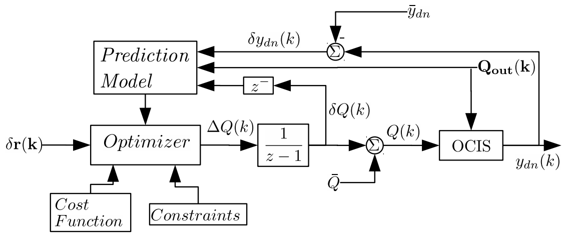

Fig. 10: Proposed structure of an MPC for an OCIS.

MPC Design: Figure 10 shows the proposed structure of the MPC, where the integral action is an essential part of this control strategy, and is added at the input of the system. Therefore, an augmented description of the discrete-time linear system (6) is given by

$$\begin{aligned}
x_1(k+1) =& a_{11}x_1(k) + a_{12}x_2(k) + b_{12}\delta Q_2(k) + b_{d_{11}}\delta Q_{out_1}(k)\\
x_2(k+1) =& x_3(k)\\
x_3(k+1) =& x_{11}(k)\\
x_4(k+1) =& a_{44}x_4(k) + a_{45}x_5(k) + b_{43}\delta Q_3(k) + b_{d_{42}}\delta Q_{out_2}(k)\\
x_5(k+1) =& x_6(k)\\
x_6(k+1) =& x_7(k)\\
x_7(k+1) =& x_{12}(k)\\
x_8(k+1) =& a_{88}x_8(k) + a_{89}x_9(k) + b_{d_{83}}\delta Q_{out_3}(k)\\
x_9(k+1) =& x_{10}(k)\\
x_{10}(k+1) =& x_{13}(k)\\
x_{11}(k+1) =& x_{11}(k) + \Delta Q_1(k)\\
x_{12}(k+1) =& x_{12}(k) + \Delta Q_2(k)\\
x_{13}(k+1) =& x_{13}(k) + \Delta Q_3(k),
\end{aligned} \tag{8}$$

then, it is obtained a classical state-space realization of the form $x_M(k+1) = A_M x_M(k) + B_M \Delta Q(k) + B_{dM}\delta Q_{out}(k)$, where $x_M(k) \in \mathbb{R}^{13}$ is the state vector; $A_M \in \mathbb{R}^{13\times 13}$ the augmented state matrix; $B_M \in \mathbb{R}^{13\times 3}$ the input matrix; $B_d M \in \mathbb{R}^{13\times 3}$ the input disturbances matrix; and $\Delta Q(k) \in \mathbb{R}^3$, the input vector. As shown in Fig. 10, the MPC has information about the outlet flows, hence the centralized controller has $FB + FF$ configuration. The prediction and control horizons chosen are $H_p = H_c = 5$. In that way, Maciejowski (2002) points out that the model for control design, assuming that all states are measurable, has the form

$$\mathbf{y(k+1) = \Psi x(k) + \Upsilon \Delta Q(k) + \Omega Q_{out}(k)}, \tag{9}$$

where $\mathbf{x(k)} = [x_M(k \mid k)\, x_M(k+1 \mid k) \dots x_M(k+5 \mid k)]^\top$, $\mathbf{\Delta Q(k)} = [\Delta Q(k \mid k)\, \Delta Q(k+1 \mid k) \dots \Delta Q(k+5 \mid k)]^\top$, $\mathbf{Q_{out}(k)} = [Q_{out}(k)\, Q_{out}(k+1) \dots Q_{out}(k+5)]^\top$, $\mathbf{\Psi} \in \mathbb{R}^{15\times 13}$, $\mathbf{\Upsilon} \in \mathbb{R}^{15\times 15}$, and $\mathbf{\Omega} \in \mathbb{R}^{15\times 15}$.

The optimization problem to be solved consists of finding the signal control $\Delta Q(k)$ that minimizes the deviation of the estimated controlled variable from the upcoming reference values and minimize the change in the control-action variable (Le-Duy-Lay et al., 2017). In this sense, the objective function for the MPC-based closed-loop scheme is given by

$$\begin{aligned}
\mathbf{V(k)} =& \|\delta\mathbf{r(k)} - \Psi\mathbf{x(k)} - \Upsilon\mathbf{\Delta Q(k)} - \Omega\mathbf{Q_{out}(k)}\|^2{}_{\mathcal{Q}}\\
&+ \|\mathbf{\Delta Q(k)}\|^2{}_{\mathcal{R}},
\end{aligned} \tag{10}$$

where $\delta\mathbf{r(k)} = [\delta r(1)\, \delta r(2) \dots, \delta r(5)]^\top$ is the reference vector, and $\mathcal{Q}$, $\mathcal{R}$ are diagonal weighting matrices. This test has been developed with diagonal values of 10 and 1 for $\mathcal{Q}$ and $\mathcal{R}$ respectively. Assuming that there is a dynamic behavior in the master-slave flow control, in this problem constraints in maximum flow variations are imposed. The restrictions are expressed in the form $-0.01 \leq \mathbf{\Delta Q(k)} \leq 0.01$, which means that in one unit of time the flow can only change by $0,01\text{m}^3/\text{s}$. Finally, the optimization problem is formulated as a quadratic programming problem (Maciejowski, 2002), which is solved with the interior-point-convex algorithm in Matlab (MATLAB, 2019).

PI + Smith Predictor Design: Figure 11 shows the structure of a PI + Smith predictor control for a channel i, where a distributed control architecture is proposed. Each $PI_i(z)$ controller is designed from the transfer function that describes the dynamic behavior of the channel, where the linearized system has output $\delta y_{dn_i}(k)$, input $\delta Q_i(k - \lfloor\frac{\tau_i}{\tau_s}\rceil)$, and the inputs $\delta Q_{i-1}(k)$ and Q_{out_i} are assumed to be disturbances. The operator $\lfloor . \rceil$) indicates the nearest integer, and the discrete-time delay associated to a transfer function can be denoted by $z^{-\lfloor\frac{\tau_i}{\tau_s}\rceil}$. However, in order to maintain the uniformity of the presented control strategies, z^- is used to indicate the time delay associated with a transfer function. Therefore, the transfer function that describes the channel i is given by

$$\frac{\delta y_{dn_i}(z)}{\delta Q_i(z)} = G_i(z) z^-. \tag{11}$$

Here, $G_i(z) = \frac{\tau_s}{A_i z + \tau_s - 1}$ is used for designing the $PI_i(z)$ controller, obtaining a proportional gain $kp_i = 1$ and an integral gain $ki_i = \frac{\tau_s}{2A_i}$. Moreover, $G_i(z)z^{-}$ is used to build the predictor with output $\hat{y}_{dn_i}(k)$ and input $\delta Q_i(k)$. In this control system, the objective is to minimize the tracking and prediction error by using the variation of $Q_i(k)$, which classically includes the $\boldsymbol{PI}$ controller output ($\delta Q_i(k)$), and the operation point ($\bar{Q}_i$). In this design, it is proposed to compensate the amount of flow required by the neighbor channel $\delta Q_{i-1}(k)$ and outlet flows $Q_{out_i}(k)$, obtaining a distributed and $\boldsymbol{FB} + \boldsymbol{FF}$ architecture with a control law given by

$$Q_i(k) = \bar{Q}_i + \delta Q_i(k) + \delta Q_{i-1}(k) + Q_{out_i}(k). \qquad (12)$$

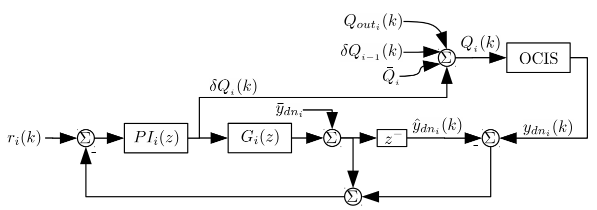

Fig. 11: Proposed structure of a PI control + Smith predictor control for OCIS.

Results The tracking behavior of the three approaches, evaluated on the nonlinear system, is shown in Fig. 12, where all of them show adequate performance. Additionally, it is seen that the PI + Smith predictor shows high decoupling behavior for reference changes at upstream channels but low decoupling behavior for reference changes at downstream channels. This is due to the fact that the control law in (12) maintains a mass balance by the addition of changes at the upstream flow $Q_{i-1}(k)$. The decoupling behavior of the LQR and MPC controllers is uniform for references and outlet flows changes at both upstream and downstream channels. Also, in Fig. 12, it is observed that the control signals of the LQR and PI controllers are more aggressive than the control signal computed by the MPC controller. One advantage of the MPC is the possibility of including constraints in the control signal, therefore, the MPC shows the less aggressive control signal, obeying the flow variation constraint. Moreover, in Fig. 12 it is possible to see the control prediction effect, where the control signal starts before the change in the reference signal. The disturbances-rejection behavior of the system controlled with MPC, LQR, and PI + Smith predictor is shown in Fig. 13. As shown in the figure, the disturbances Q_{out_i} have permanent and normally distributed components. Again the PI + Smith predictor shows high decoupling behavior for permanent disturbances at upstream channels but shows a low decoupling behavior for permanent disturbances at downstream channels. In general, the LQR presents the best

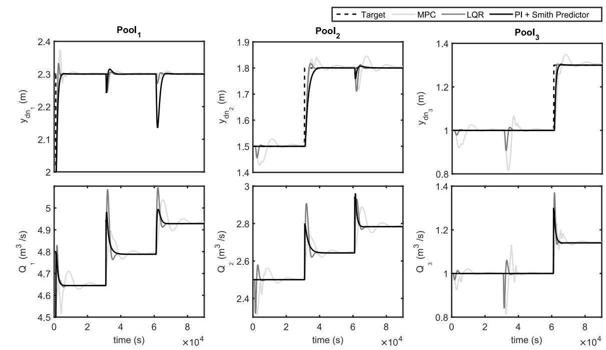

Fig. 12: Tracking behavior of the system controlled with MPC, LQR and PI + Smith predictor. The black dashed lines represent the targets for y_{dn}.

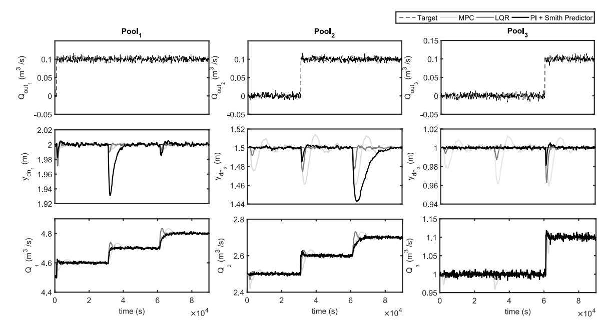

Fig. 13: Disturbances-rejection behavior of the system controlled with MPC, LQR and PI + Smith predictor.

disturbances rejection and the MPC the less aggressive control signal. Moreover, according to the results, the three control strategies have shown appropriate behavior and can be implemented following systematic procedures. Furthermore, it must be highlighted that the LQR and MPC strategies also can be performed using distributed and $\boldsymbol{FF} + \boldsymbol{FB}$ configurations. On the other hand, the use of the ID model as a design model shows that this strategy is successful in designing conventional control strategies with multiple control configurations. However, due to the over simplicity of the ID modeling strategy, in order to assert the suitability of control strategies designed from simplified models, the development of control strategies comparisons on real systems is necessary.

7. Conclusions

In this paper, a review in modeling and control of open-channel irrigation systems has been presented. The review has been developed around a proposed classification for modeling approaches and another classification for control strategies. Moreover, a discussion with the aim of establishing suitable modeling and control approaches and the research gaps that need to be addressed is also established. In this way, from the discussion, it is concluded that most of the simplified and approximated models reported are an oversimplification of the open-channel irrigation systems, which are not useful to test the behavior of the controllers under realistic conditions, and the gray-box models are an attractive option for control systems design and testing. However, most of the gray-box models reported are only useful for systems with weir structures in free-flow. Additionally, in the discussion, a classification of the control approaches for open-channel irrigation systems is given, and the most common control approaches are presented, highlighting that the most common control objective is to maintain a constant depth at the end of the channels. MPC is the control strategy that is getting the highest and growing attention, and towards increasing the efficiency of the open-channel irrigation systems, the new control approaches must be focused on increasing the efficiency of the systems reducing losses due to leaks, evaporation, and overflows.

Furthermore, the review presents a case study with three channels, which illustrates the development of a control-oriented modeling strategy, and the design of the most common control approaches. In the case study, three control strategies are explained and implemented, showing their procedure, specific results, and features. In the case study it is highlighted that with the purpose of accomplishing with the habitual task of maintaining a constant depth at the end of the channels, any of the three control strategies can be used.

Finally, the open-channel irrigation systems have a high environmental and agricultural impact and the theoretical contribution to open-channel irrigation systems control also contributes to saving water. According to the review and the results obtained, the development of new control-oriented models, the research in the estimation of unknown inputs, and the development of more innovative control strategies for open-channel irrigation systems are still open problems that must be addressed in the short term.

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