# Model Predictive Control of water resources systems: A review and research agenda

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# Model Predictive Control of Water Resources Systems: A Review and Research Agenda

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**Abstract**

Model Predictive Control (MPC) has recently gained increasing interest in the adaptive management of water resources systems due to its capability of incorporating disturbance forecasts into real-time optimal control problems. Yet, related literature is scattered with heterogeneous applications, case-specific problem settings, and results that are hardly generalized and transferable across systems. Here, we systematically review 149 peer-reviewed journal articles published over the last 20 years on MPC applied to water reservoirs, open channels, and urban water networks to identify common trends and open challenges in research and practice. The three water systems we consider are inter-connected, multi-purpose and multi-scale dynamical systems affected by multiple hydro-climatic uncertainties and evolving socioeconomic factors. Our review first identifies four main challenges currently limiting most MPC applications in the water domain: (i) lack of systematic benchmarking of MPC with respect to other control methods; (ii) lack of assessment of the impact of uncertainties on the model-based control; (iii) limited analysis of the impact of diverse forecast types, resolutions, and prediction horizons; (iv) under-consideration of the multi-objective nature of most water resources systems. We then argue that future MPC applications in water resources systems should focus on addressing these four challenges as key priorities for future developments.

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## 1. Introduction

Adaptive water resources management is a priority for resilient development and adaptation to increasing hydro-climatic variability and socio-economic transformations (Brears, 2018; Şen, 2021; Stevenson et al., 2022; Zhao and Boll, 2022). Global physical and socio-economic changes add pressure on governments and policy-makers to urgently address water-related multi-sector challenges including energy and food security, human and environmental health, economic development, and climate change mitigation and adaptation (e.g., GWP, 2021; Srivastava et al., 2022; Miralles-Wilhelm, 2022). To address these challenges, improve the sustainability and efficiency of water resources management, and adapt to transformative changes, new opportunities may come from adaptive control techniques and hydro-meteorological forecasts (Coelho and Andrade-Campos, 2014; Ding et al., 2018; Dobson et al., 2019; Yuan et al., 2019; Wu et al., 2020b; Abioye et al., 2020; Giuliani et al., 2021; Şen, 2021; Bwambale et al., 2022).

Control methods and tools have been used in the water management community to design optimal water resources operations for several decades already, since the 1955 Harvard Water Program (see Reuss (2003) for a historical perspective, the pioneering work by Maass et al. (1962) and the reviews in Yeh, 1985; Malaterre, 1995; Malaterre et al., 1998; Labadie, 2004; Mareels et al., 2005; Castelletti et al., 2008b; Coelho and Andrade-Campos, 2014; García et al., 2015; Creaco et al., 2019; Macian-Sorribes and Pulido-Velazquez, 2020; Van Der Werf et al., 2022). Yet, this is still a very active research field, as water systems are uncertain dynamic systems with challenging features that make the use of optimal control tools particularly complex. First, water systems' disturbances and related risks are ever-changing, as the variability induced by changing hydro-climatic conditions has been expanding in recent decades (e.g., Hall et al., 2014; Sreeparvathy and Srinivas, 2022), alongside the frequency and intensity of extreme events that are being exacerbated with climate change (Trenberth et al., 2014; IPCC, 2021; Stevenson et al., 2022; Gründemann et al., 2022). Second, human pressure on water resources has been augmenting with population and socio-economic growth, leading to increased water and energy demands at the global scale (e.g., van Ruijven et al., 2019; Boretti and Rosa, 2019; Wu et al., 2020c). This, in turn, has shifted decision makers' preferences and risk perception (e.g., Poff et al., 2016; Giuliani et al., 2021). Third, water systems usually serve multiple stakeholders with often conflicting and time-evolving objectives (Soncini-Sessa et al., 2007), which makes the exploration of trade-offs essential (e.g., Reed et al., 2013).

The advantages of using real-time adaptive model-based control techniques are evident in the context of hydro-climatic and socio-economic changes, as the use of forecasts unlocks the control potential to anticipate and, therefore, adapt to changes in the system's characteristics and disturbances. These approaches can be grouped under the umbrella of Model Predictive Control (MPC) (Bertsekas, 2005; Scattolini, 2009), which is a popular approach, mostly well-established for industrial applications (e.g., Qin and Badgwell, 2000; Forbes et al., 2015; Schwenzer et al., 2021) yet attracting increasing attention from the water systems community (e.g., Giuliani et al., 2021) due to recent advances in monitoring and forecasting systems and increasing computational capabilities (e.g., Wu et al., 2020a). Hydro-meteorological forecasts have constantly been improving in quality and accessibility over the last few decades (e.g., Buizza, 2019; Wu et al., 2020a). Similarly, hydrological and water systems' models have been substantially refined in recent years, allowing both the representation of physical processes at the highest resolution (e.g., Bierkens et al., 2015; Nair et al., 2020) and the efficient emulation of high-fidelity models via surrogate models based on machine learning techniques (e.g., Wu et al., 2014; Miro et al., 2021; Huang et al., 2021). Today, it is possible to assimilate earth observations and operational forecasts in real-time and run optimization and simulation models within a reasonable time thanks to recent technological advances (Blair et al., 2019; Creaco et al., 2019; Camporese and Girotto, 2022; Baardman et al., 2022).

In this context, we believe that a review of MPC applications to water management problems is timely and important to stimulate reflections on MPC benefits and challenges in the water sector and set the path for further research and practice developments. While previous reviews focused on discussing the use of different optimal control methods in specific water systems (e.g., water reservoirs), here we contribute a comprehensive analysis of the most recent advancements in MPC for different types of water systems. The heterogeneous features of these systems introduce distinct challenges to optimal control techniques and often require diverse MPC approaches. In this review, we focus on three key types of interconnected water systems designed and operated to store, convey, and distribute water for human and environmental needs as well as to manage sewer and drainage flow at the basin to urban scales: water reservoirs, open channels, and urban water networks. To build our comprehensive review of 149 peer-reviewed journal articles, we follow an automatic search procedure and then refine the paper selection using a set of eligibility criteria, as detailed in the Methods.

The Methods section first recalls the MPC methods used for water systems' operations. Then, the three types of water systems within the scope of this review are introduced, explaining why these systems are relevant and detailing the models used in the MPC applications. The Results Section then provides a detailed summary of the reviewed papers across the three types of water systems. Finally, the Discussion and Conclusions Sections summarize the limitations and merits of the applications reviewed and highlight the most urgent needs for future developments.

## 2. Methods

### 2.1. Model Predictive Control

Model Predictive Control is a control strategy based on the sequential, online resolution of multiple open-loop control problems defined over a finite, receding time horizon (Bertsekas, 2005). At each time step, the resolution of an MPC problem yields a sequence of optimal control actions (i.e., the releases for reservoirs, gate openings for channels, etc.) over the future horizon $[t, t+h]$, given a predicted trajectory of the disturbances over the same horizon. The optimization is generally formulated considering a single objective; when the problem involves multiple objectives (e.g., water supply, hydropower production, flood control, environmental protection, irrigation, transport, etc.), these are generally aggregated using a scalarization function (e.g., weighted combination) or via the lexicographic goal programming technique in cases where there is a clear hierarchy of priorities across the objectives (e.g., Horvath et al., 2022). The online optimization scheme is reiterated forward in time over a receding horizon during the operational life of the system. After each optimization, only the first control action of the optimized control sequence is actuated, before reiterating the optimization at the next time step. Through this reiteration of the model-based optimization, MPC determines the control law implicitly in a closed-loop form, as it computes the optimal control action at each time step $t$ based on the observed state of the system ($\mathbf{x}_t$). The current state of the system can be directly observed in most of the cases for the water systems considered in this review. A state estimator is needed otherwise.

MPC requires a model of the system (see Section 2.2), also known as *internal* or *prediction* model, to predict the effect of control actions on the controlled system's dynamics, and to determine the set of actions that yield the optimal performance with respect to the considered objectives subject to physical and operational constraints. The choice of the model plays a major role in the performance yielded by the MPC. The flexibility of the direct use of any models available for the systems to be controlled is one of the main advantages of this approach, particularly in terms of controlling highly non-linear systems. The requirement for computational efficiency is the main factor that can limit the use of fully physically-based models of large-scale complex water systems like urban water networks, for which reduced-order data-driven models can be developed to be used in MPC (see Section 3.3). The flexibility in working with (nonlinear) constraints is another advantage of MPC compared to other control methods. And this advantage is particularly relevant for water systems, as explicit physical constraints (with non-linearities), like limits of actuators, or legal constraints, like a minimum release from reservoirs, are often required.

Another advantage of MPC with respect to other control approaches is the mitigation of the curse of 'dimensionality' (Bellman, 1957) that limits the applicability of Dynamic Programming family methods to large water systems because of the challenges associated with the computation of the value functions for increasing dimensions of state and control vectors. Moreover, the use of real-time information and probabilistic/ensemble forecasts in the optimization process allows MPC to adapt to evolving external conditions and mitigate the impacts of uncertain extreme events.

Different configurations of MPC exist depending on how they handle the control of multiple actuators in large-scale systems (centralized, decentralized, or distributed MPC), the parameter estimation problem (adaptive or non-adaptive MPC), and the uncertainty in disturbance forecasts (deterministic or robust and stochastic MPC; see Sections 2.1.1 and 2.1.2).

A centralized MPC configuration assumes that a single controller processes measurements from all sensors/gauges and determines optimal actions to be applied by all actuators. However, water systems are usually spread over large, often transboundary regions, and several water boards can be involved in their management. In such large systems, centralized management may become unfeasible or computationally cumbersome, and may also be undesirable with regard to system reliability, scalability, and responsiveness. Thus, multi-agent control, whereby the control effort is divided among local agents (also referred to as controllers), each in charge of part of the overall system, emerges as a possible way to circumvent the drawbacks arising from centralized implementations. Two main criteria by which to classify multi-agent control approaches are the existence of communication links and hierarchy among local controllers. On the one hand, an approach is said to be decentralized if interactions among local controllers are neglected, and distributed if communication links among local controllers are enabled for the sake of improved overall performance, although at the expense of increased computation times. On the other hand, an approach is said to be single-level if all local controllers are at the same hierarchical level, and multi-level if a subset of local controllers has ascendancy over the rest.

Regarding the problem of reducing model uncertainties, in standard (non-adaptive) MPC, the model used for prediction is often assumed to be accurate and fixed in time, while only its state is updated. However, by using a fixed model parameterization the changing uncertainties within the system are not taken into account, which can reduce the MPC performance. In contrast, in adaptive MPC, the model parameters can be updated online by using available measurements, and the estimation problem is addressed by including a parameter estimation procedure as part of the control strategy. The control action is then calculated not only based on the estimated current state but also on the updated model, which can help reduce the dynamic model uncertainties affecting MPC (Lemos et al., 2009).

*2.1.1. Deterministic MPC*

In cases where a single deterministic prediction of the systems' disturbances is available, the formulation of the (single-objective) MPC problem over the prediction horizon ($h$), to be solved at each control time step, is as follows:

$$\min_{u_t,\dots,u_{t+h}} \sum_{\tau=t}^{t+h-1} g_\tau(\boldsymbol{x_\tau}, \boldsymbol{u_\tau}, \hat{\varepsilon}_{\tau+1}) + g_{t+h}(\boldsymbol{x_{t+h}}) \tag{1}$$

subject to:

$$\boldsymbol{x_{\tau+1}} = f_\tau\left(\boldsymbol{x_\tau}, \boldsymbol{u_\tau}, \hat{\varepsilon}_{\tau+1}\right) \tag{2}$$

$$c\left(\boldsymbol{x_\tau}, \boldsymbol{u_\tau}, \hat{\varepsilon}_{\tau+1}\right) \leq 0 \tag{3}$$

$$\hat{\boldsymbol{\varepsilon}}_{\tau+1} \quad \text{given for } \tau = t, \dots, t+h-1 \tag{4}$$

$$\boldsymbol{x_t} \quad \text{given} \tag{5}$$

where: $\boldsymbol{x}_\tau$ is the state of the system at time step $\tau$ (e.g., the reservoir storage, the water level in channels, and the state of other dynamical components); $\boldsymbol{u}_\tau$ is the control vector including all control actions for the actuators (e.g., gates or pumps); $\hat{\boldsymbol{\varepsilon}}_{\tau+1}$ is the deterministic forecast of the system's disturbances provided by a prediction model for each time step $\tau$ over the prediction horizon $[t+1, t+h]$; $g_\tau(\cdot)$ is a time-separable cost function associated with the transition from time step $\tau$ to $\tau+1$; $g_{t+h}(\cdot)$ is a penalty function associated with the final state ($\boldsymbol{x}_{t+h}$ ) that represents the future costs beyond the prediction horizon. It should be noted that the control horizon, i.e. the time span for which the control inputs are allowed to vary, can be shorter than the prediction horizon, though often they are assumed to be equal as in Eq. 1.

The optimal control problem 1 is subject to the dynamic constraints provided by the state transition function (Eq. 2) along with different types of physical constraints (e.g., limits of actuators) and operational/legal ones (e.g., minimum environmental flows) that can be expressed as (non linear) inequality constraints (Eq. 3).

#### *2.1.2. Robust and Stochastic MPC*

One of the limitations of Problem (1) is that it requires the availability of the sequence of future system disturbances $\{\hat{\varepsilon}\}_{t+1}^{t+h}$, which is unrealistic to expect to be perfect in many practical situations. To deal with this issue, the MPC framework includes strategies that handle uncertainties in a robust manner via worst-case formulations, e.g., min-max and robust MPC. While these methods guarantee the satisfaction of the problem constraints as long as some assumptions are satisfied (mainly, that disturbances are bounded), they also generally lead to very conservative control policies because a worst-case scenario approach is followed. To remedy this situation, stochastic MPC approaches exploit the characterization of the forecasted uncertainties, to obtain a trade-off between closed-loop constraint satisfaction and performance. Stochastic MPC approaches typically employ so-called *chance constraints*, i.e., constraints that should be satisfied with a predefined probability level (Mesbah, 2016). Thus, occasional violations of the constraints might occur, but system performance will be increased during normal system operation because the controller will be allowed to work closer to the constraints in comparison to worst-case approaches.

Here, we propose a classification of existing robust and stochastic MPC approaches used in the water systems literature so far into two categories, based on the way the knowledge of the probability distribution function (pdf) of the disturbances is implemented into the optimization problem: (i) explicit robust and stochastic approaches, that use the explicit information on the pdf, and (ii) implicit approaches, that rely on a set of scenarios (or *ensemble forecasts*) which encode information about the disturbance evolution and its uncertainty in an implicit manner.

(i) Explicit approaches, require an explicit (probabilistic) characterization of the disturbance behaviour. A classical strategy to deal with uncertainty explicitly is the use of *Open-loop feedback control* (OLFC), as introduced by Bertsekas (1976). This approach presents the future disturbances according to their probability distribution and computes the objectives through a function to filter the disturbances (e.g., expected value). The OLFC performance can be improved by adopting a partial open-loop feedback control (POLFC) formulation (e.g., Castelletti et al., 2008a; Pianosi and Soncini-Sessa, 2009), which explicitly assumes that in the future the state of the system will be measured and a new problem will be reformulated. The POLFC problem, therefore, computes at each time step the optimal release decision for the first time step reflecting first-step uncertainty and the optimal operating policy for the following time steps.

(ii) Implicit approaches rely on the use of a set of scenarios of the disturbances. The set of scenarios can be either built using data from previous realizations or using real-time probabilistic forecasts. A classical implicit approach that uses scenarios in MPC is the *Scenario-based MPC* which allows optimizing the system behaviour for several disturbance realizations. This approach has been generalized in Calafiore and Campi (2006); Calafiore and Fagiano (2013a,b), and has been applied to water systems in van Overloop et al. (2008); Tian et al. (2019); Velarde et al. (2019); Tian et al. (2017b). An interesting feature of this approach is that multiple models can be considered, thus allowing to consider model uncertainty in addition to disturbance uncertainty. The scenario-based MPC approach can be extended via the *Tree-based MPC* (TB-MPC) formulation to provide the controller with enhanced closed-loop control capabilities so that it can adapt to future events, as uncertainty is resolved via bifurcation points along the prediction horizon, as first applied to water systems in Raso et al. (2014). Implicit approaches are particularly relevant for water systems as the forecasts are often provided in the form of an ensemble of multiple time series, usually generated by running the forecast model multiple times with perturbed initial conditions or using multiple models. Given their capacity to account for the inherent forecast uncertainty, ensemble forecasts have become a standard in hydro-meteorological forecasting (Gneiting and Raftery, 2005; Buizza, 2019; Zhao et al., 2021). This ensemble is then transformed into a tree where similar ensemble members are bundled together into one trajectory (branch) up to the point when some of them start to significantly diverge from the others. The tree structure is then used to optimize a *control tree* defining a distinct control sequence for each branch. Control sequences are constrained to be the same up to the time when two ensemble members diverge. Examples of applications of TB-MPC can be found in Maestre et al. (2013); Raso et al. (2014); Ficchi et al. (2016); Uysal et al. (2018a).

Explicit knowledge about the disturbance (pdf) might be available and can used to build a set of scenarios for implicit approaches, such as multi-scenario MPC or TB-MPC, so as to achieve approximate robust MPC strategies (Lucia et al., 2013). Alternatively, one may proceed the other way around, by using historical data (e.g., previous realizations of the disturbances or reforecasts) to generate an explicit model (possibly with some limitations) and use that in explicit stochastic approaches.

Finally, stochastic approaches can be considered robust as well if very strict requirements are imposed regarding the probability of closed-loop constraint violation. As the imposed probability of constraint violation tends to zero, the controller becomes more and more robust as it needs to increase the safety margin with respect to the problem constraints. For this reason, there are some articles in the literature that present stochastic approaches from a robustness viewpoint (Shang et al., 2020; Chen et al., 2021; Chen and You, 2021).

### *2.2. Models for water systems applications*

This section provides an overview of the models used for representing the different water systems considered in this review, namely water reservoirs, open channels, and urban water networks. It is worth mentioning that despite we illustrate and discuss these systems separately, they are often interconnected with water reservoirs feeding either open channels and/or urban water networks.

#### *2.2.1. Water reservoirs*

A water reservoir is a regulated storage or lake, controlled by a dam that either blocks the flow of a watercourse that is drained from upstream catchments (in-stream reservoir) or creates a retention basin collecting water supplied by an adjoining stream, a canal, pipeline or aqueduct (off-stream). Reservoirs can be part of networks of different levels of complexity, with two or more reservoirs in

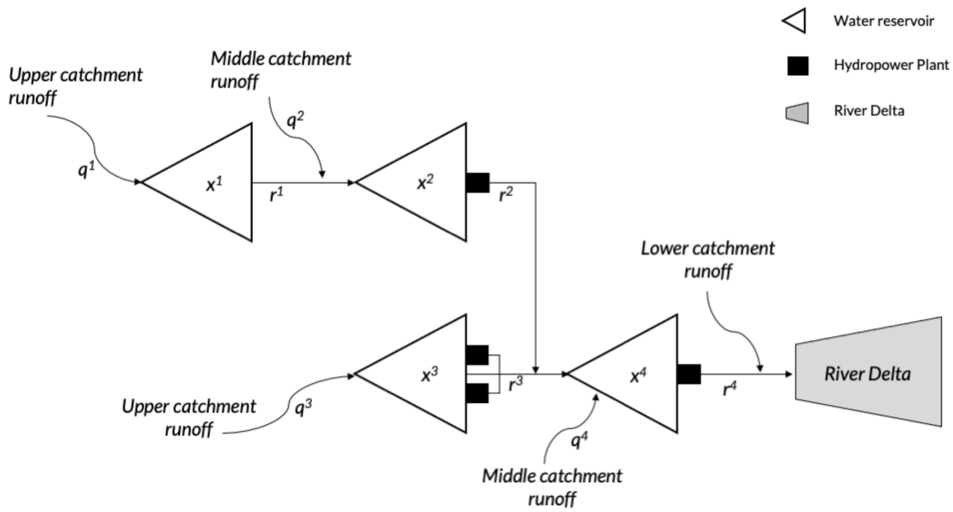


Figure 1: Schematic representation of a multi-reservoir network, adapted from the Zambezi river system's scheme reported in Giuliani and Castelletti (2013).

parallel or in series (see Figure 1 for a schematic representation), connected with water users via natural or artificial canals.

Reservoirs are usually multi-purpose systems, serving power plants, irrigation districts, urban and industrial water users, as well as contributing to other targets like flood control, environmental management, navigation, water quality, etc. Traditionally, reservoir control is implemented by a human operator that can act based on static rule curves or control actions suggested by a Decision Support System (DSS) in real-time. Since the control time step is discrete, the model for a reservoir is typically written in time-discrete form too, even though the physical processes involved in the system are time-continuous. The control time step varies based on the type of systems and objectives, with control frequencies typically ranging from hourly or daily for smaller systems and for flood control or hydropower generation, to monthly for large systems and for water supply objectives. The generic model for a system of $N$ reservoirs is based on the mass-balance equation describing the dynamics of the water storage at each reservoir $j$ as:

$$x_{t+1}^{j} = x_t^j + q_{t+1}^j - r_{t+1}^j \tag{6}$$

where: $x_t^j$ is the state of reservoir $j$ at time step $t$, i.e., the reservoir storage; $q_{t+1}^j$ is the net inflow volume (i.e., inflow and direct precipitation minus evaporation and seepage losses) from time step $t$ to $t+1$; $r_{t+1}^j$ is the actual release from the reservoir in the same time interval. In the notation in Eq. 6, the time subscript of each variable indicates the time instant when the value is deterministically known. The reservoir storage is measured at time step $t$ and thus is denoted as $x_t^j$, while the net inflow and the actual release are denoted as $q_{t+1}^j$ and $r_{t+1}^j$, respectively because they can be known only at the end of the time interval. For multi-reservoir systems, the global model is obtained by aggregating the models of the $N$ reservoirs that compose it, i.e., all the variables in Eq. 6 become vectors (e.g., $\mathbf{x}_t$, $\mathbf{q}_{t+1}$) and the network topology can be represented by an incidence matrix (Giuliani et al., 2021).

The actual release $r_{t+1}^j$ is a function of the control variable $u_t^j$ (i.e., the release decision at time step $t$), of the storage $x_t^j$ and of the net inflow $q_{t+1}^j$:

$$r_{t+1}^j = R_t^j\left(x_t^j, u_t^j, q_{t+1}^j\right) \tag{7}$$

where the function $R_t^j(\cdot)$ is called the release function and it is a nonlinear function, which binds the actual release within a range of physical acceptability. The range is defined by the minimum and maximum releases that would occur from time step $t$ to $t+1$ by keeping all the sluice gates completely closed and open, respectively (Castelletti et al., 2008b). Thus, the release function allows for the inclusion of physical constraints on reservoir storage and release into the model. The actual release may differ from the control decision when the available water is not sufficient to realize the decision or when a spill takes place. The release function is inherently stochastic because between the time step $t$ at which the release decision is taken and the time step $t+1$ at which the control action is completed, the uncertain net inflow $q_{t+1}^j$ affects the reservoir storage.

The net inflow $q_{t+1}^j$ is an aggregation of several hydro-meteorological contributions including upstream and lateral flows from tributaries and runoff, direct precipitation over the reservoir minus evaporation and infiltration losses. The net inflow is often modelled as a system disturbance (i.e., $q_{t+1}^j{=}\varepsilon_{t+1}^j$ ), aggregating multiple sources of uncertainty, though its contributions can also be separately modelled as distinct disturbances. On the other hand, the hydrologic processes contributing to the net inflow can be represented using dynamic hydrological models of different types, from conceptual to physically-based, lumped or spatially distributed, deterministic or stochastic models. Data-driven alternatives or simple statistical models are often preferred because of their computational efficiency (e.g., Wang et al., 2009) and, recently, efforts are being made to move towards hybrid models (a combination of pure data-driven and process-based models) that can be more interpretable by users (e.g., Chakraborty et al., 2021). These models can be used to provide a set of deterministic or stochastic forecasts of the disturbance, that can be issued before every control time step and used in an optimal control problem.

#### *2.2.2. Open channels*

Open-channel systems are large-scale networked systems that consist of natural rivers and artificial canals and serve multiple purposes. As part of the integrated urban water management cycle, open-channel systems can be used to convey treated water to consumer areas, which may then be supplied to consumers (using pressurized pipeline networks) or used for irrigation purposes. Open-channel systems can also be employed for freight and passenger transportation, provided that water depth and width are sufficient. Moreover, the watercourse should not be interrupted too frequently by elements that must be avoided, e.g., reefs, rocks and sandbanks, and bridges should have sufficient clearance. Although not strictly in the scope of this paper, it is interesting to note that research on inland waterborne transport is attracting increasing attention, as it is one of the most environmentally friendly and cost-effective transport modes. A schematic representation of an open-channel system is given in Figure 2, which shows its main constitutive elements. On the one hand, canals are stretches of the watercourse bounded between two control structures. On the other hand, actuators are hydraulic infrastructure, e.g., gates, weirs and dams, available for water control purposes (see examples above). Finally, nodes represent canal junctions, i.e., locations wherein a stream flows into or branches off from the main stream (these are known as tributary and distributary, respectively).

Open-channel dynamics are most accurately described by the Saint-Venant equations, a set of coupled nonlinear partial differential equations that can be formulated as follows (Litrico and Fromion, 2009):

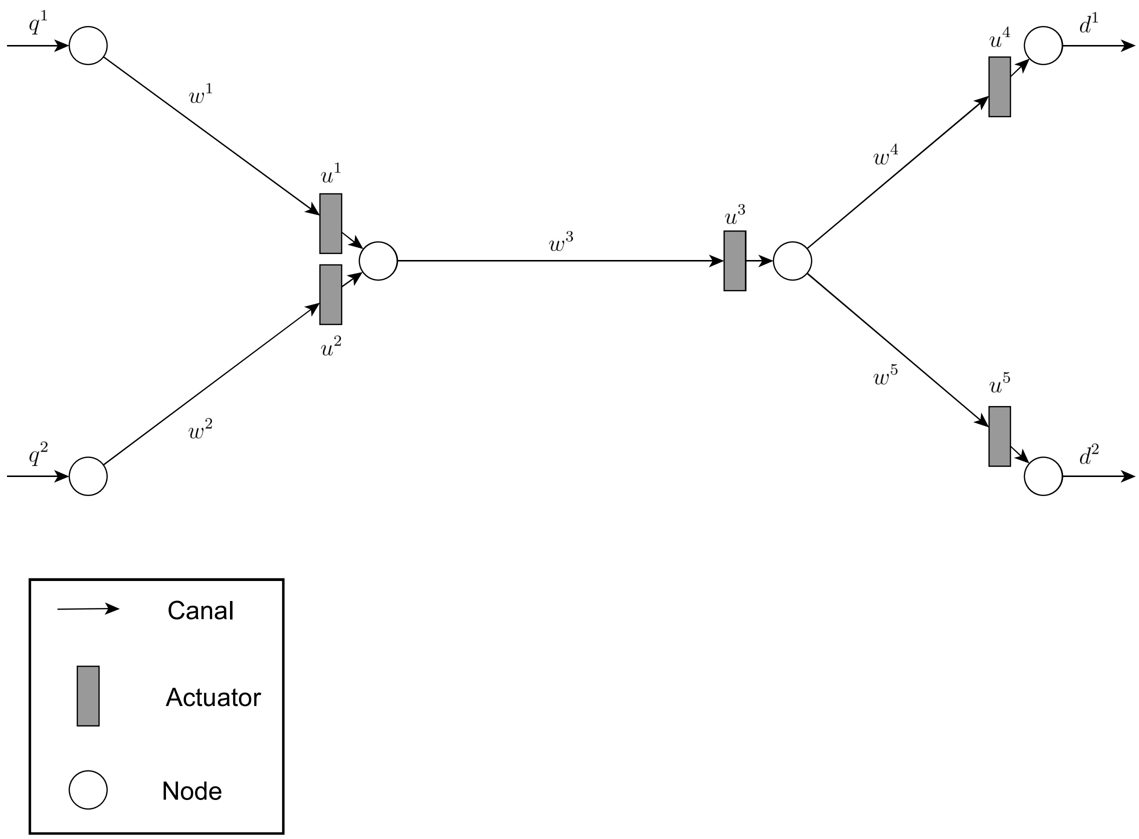


Figure 2: Schematic representation of an open-channel system.

$$\frac{\partial A(l,t)}{\partial t} + \frac{\partial Q(l,t)}{\partial l} = 0, \tag{8a}$$

$$\frac{\partial Q(l,t)}{\partial t} + \frac{\partial}{\partial l}\left(\frac{Q^2(l,t)}{A(l,t)}\right) + gA(l,t)\left(\frac{\partial Y(l,t)}{\partial l} + S_f(l,t) - S_b(l)\right) = 0. \tag{8b}$$

Equations (8a) and (8b) represent the mass and momentum conservation equations, respectively, the latter comprising inertia, advection, gravitational force and friction force terms. Moreover, $l$ is the longitudinal abscissa (continuous independent variable), $t$ is the time (continuous variable), $A(l,t)$ is the wetted area [m$^2$], $Q(l,t)$ is the discharge [m$^3$/s] across section $A$, $V(l,t) = Q(l,t)/A(l,t)$ is the average velocity [m/s] in section $A$, $Y(l,t)$ is the water depth [m], $S_f(l,t)$ is the friction slope [m/m], $S_b(l)$ is the bed slope [m/m] and $g$ is the gravitational acceleration [m/s$^2$].

Equation (8) must be completed with initial and boundary conditions. On the one hand, the initial condition is given in terms of $(Q(x,0), Y(x,0))$, for all $x \in [0,L]$, where $L$ is the length of the canal. On the other hand, boundary conditions must be chosen depending on flow characteristics: subcritical flow requires an upstream and a downstream condition; supercritical flow requires two upstream conditions; and intermediate situations require to specify one, two, or three conditions, depending on the situation (Litrico and Fromion, 2009). Furthermore, available measurements and controls must be specified. It is typically the case in practical situations that available measurements and controls are boundary water levels and gate openings, respectively (Litrico and Fromion, 2009).

Because of their accuracy, the Saint-Venant equations constitute the basis of state-of-the-art simulation software, e.g., SOBEK[1] and SICˆ2[2]. However, they are demanding in terms of computational resources and provide too much information for applications such as controlling average water levels, two facts that render their direct use impractical for control purposes (hence the variables in (8) are not directly connected with the notation introduced in Figure 2). For this reason, the use of alternative and simpler models as prediction models (i.e., internal MPC models) is commonly encountered in the literature. These simplified models generally compensate the loss of precision with a significant reduction of the computational burden, which in turn allows to use more elaborated formulations within the MPC framework. Several classes of simplified models have

[1]https://www.deltares.nl/en/software/sobek/
[2]http://sic.g-eau.net

been developed:

- Some models are obtained directly from the Saint-Venant equations, discretizing the system in space (e.g., using a staggered grid) and linearizing. The kind of discretization method employed plays a crucial role in the stability of the obtained model. On the one hand, certain time-implicit methods yield stable models regardless of the step size chosen, even for nonlinear hyperbolic systems (Hirsch, 2007). On the other hand, the stability of explicit discretization methods depends on the discretization step size (Conde et al., 2021).

- Other models are based on strong mechanistic simplifications of the behaviour of the canal dynamics:

  - One of the first proposals was the *Integrator Delay* (ID) model (Schuurmans et al., 1995, 1999), an approximation model for flow in an open channel with a backwater effect. The integrator term captures the canal volume change according to the water level variation, and the time delay indicates the required time for a disturbance generated at one end of the canal to have an effect at the other end. It is worth noting that some authors simplify the ID model even further, considering only the integrator term (I), thus assuming that the canal behaves like a reservoir.

  - A modification to the ID model was proposed by Litrico and Fromion (2004) to represent the high-frequency phenomena and thus describe a canal in any flow condition. This new model, which features a zero in the transfer function to represent the direct influence of the discharge on the water level in high frequencies, is known as the *Integrator Delay Zero* (IDZ) model.

  - The *Integrator Resonance* (IR) model was proposed by van Overloop et al. (2010b), to characterize the effect of reflecting waves on the water levels, which dominate the behaviour of the short and deep open-channel flow.

- System identification techniques have also been employed for the purpose of open-channel modelling. In particular, black-box models, which do not make use of any physical insight, have proven to perform well (Weyer, 2001; Rivas-Pérez et al., 2014).

The common feature shared by the different simplified models is the connection between discharges and water levels. However, some of these models are formulated using continuous time input-output representations (e.g., ID, IDZ and IR), and must be discretized for implementation purposes. On the other hand, models with full space-time discretization are directly described in discrete-time state-space form.

With some minor adjustments, all these models can be framed within the more general control-oriented model given below:

$$\boldsymbol{x}_{t+1} = F(\boldsymbol{x}_t, \boldsymbol{u}_t, \boldsymbol{w}_t, \boldsymbol{d}_t), \tag{9a}$$

$$0 = G(\boldsymbol{x}_t, \boldsymbol{u}_t, \boldsymbol{w}_t, \boldsymbol{d}_t). \tag{9b}$$

The variables used in Eq. (9) follow the notation introduced in Figure 2, and their meaning is as follows: the vector of states $\boldsymbol{x}_t$ contains the water levels (and possibly other terms, depending on the simplified model that is employed), $\boldsymbol{u}_t$ denotes the vector of control inputs (e.g., actuator flow or position setpoints; for an exhaustive list of control variables see Section 3.2), $\boldsymbol{w}_t$ represents the vector of uncontrollable flows due to environmental phenomena (e.g., rainfall, infiltration and percolation), and $\boldsymbol{d}_t$ is the vector of water demands (e.g., off-takes by farmers) that act as system disturbances $\boldsymbol{\varepsilon}_{t+1}$. Note that (9) includes differential and algebraic equations: the former represent the system dynamics, and the latter account for the mass balances that must hold at the nodes.

*2.2.3. Urban water networks*

The integrated urban water cycle is composed of several infrastructural and operational components, including water sources management, water treatment, water transport and distribution, sewer/wastewater collection, and rainwater/stormwater drainage systems (Loucks and Van Beek, 2017), which have the main goal of providing water for human needs reliably, efficiently, and safely, and then returning it to the environment with the lowest possible impact (Walski et al., 2003). The problem of optimal operation of large-scale urban water networks has been extensively investigated in the literature in the last 50 years (Mala-Jetmarova et al., 2017), with the main focus on water transport and distribution networks and optimal management of sewer and drainage infrastructure, beside smaller-scale applications that focus on solving local optimization problems of individual network components, such as individual pumps/pumping stations and water treatment processes in water/wastewater treatment plants.

Taking water transport and distribution networks for instance (see Figure 3 for a schematic representation), an optimal control problem is typically formulated as an optimal pump operation

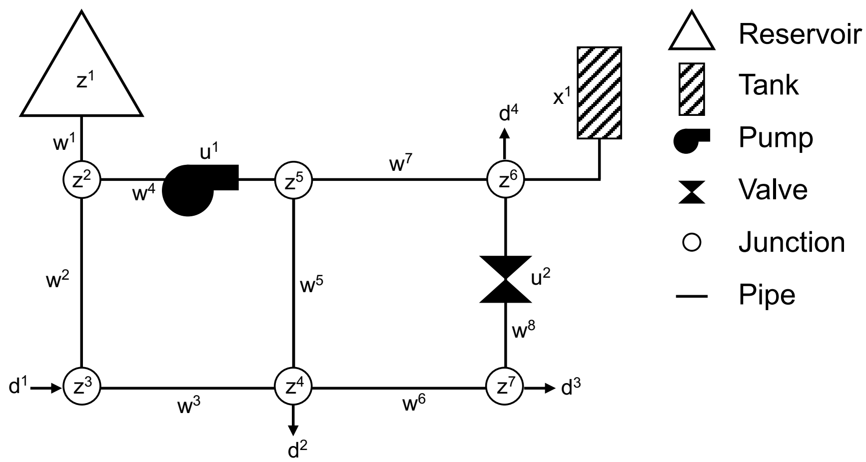


Figure 3: Schematic representation of a water distribution network, adapted from the Epanet 2: user manual (Rossman et al., 2000).

control problem targeting resources and economic savings in energy use and related cost, while ensuring that water is conveyed to final users to satisfy their water demands. Modelling a water distribution network requires modelling its main components, which can be classified into *nodes* - which include demand junctions (where water leaves or enters the network), reservoirs (water sources), and tanks (where water is stored) - and *links* - which include pipes connecting different nodes and valves and pumps, which are the actuators in the system to be controlled. Accounting for all aforementioned system components, a control-oriented model of a water distribution network can be formulated as in Wang et al. (2017):

$$\boldsymbol{x}_{t+1} = F(\boldsymbol{x}_t, \boldsymbol{z}_t, \boldsymbol{u}_t, \boldsymbol{w}_t, \boldsymbol{d}_t), \tag{10a}$$

$$0 = G(\boldsymbol{x}_t, \boldsymbol{z}_t, \boldsymbol{u}_t, \boldsymbol{w}_t, \boldsymbol{d}_t), \tag{10b}$$

where the dynamic states in vector $\mathbf{x}_t$ are the water storage levels (heads) of the network tanks at time step $t$, the algebraic states $\mathbf{z}_t$ is the vector of hydraulic heads in all other nodes of the network, resulting from flow balance, $\mathbf{u}_t$ is the vector of control inputs (pump operations and valve status), and $\mathbf{w}_t$ is the vector of non-controllable flows through pipes. $\mathbf{d}_t$ is the vector of water demand intended as system disturbances $\boldsymbol{\varepsilon}_{t+1}$. Pump and valves might vary in type and size. For instance, pumps might be with fixed-speed or variable-speed drives, valves might be pressure modulating or pressure reducing valves, non-return valves, head control, etc., which should be accounted for in modelling such components, as their characteristics also constrain the type and range of available controls.

The above discrete-time model includes difference and algebraic equations, based on mass and energy conservation. The mass balance should be guaranteed at the network nodes, implying that the flow rate of water $q$ in node $n$ from all its connected pipes $p$ is balanced by the actual demand in that node $d_t^{act,n}$ in each time step $t$ (Rossman et al., 2000):

$$\sum_{p \in P_n} q_t^{p,n} - d_t^{act,n} = 0. \tag{11}$$

Energy conservation is formulated to satisfy the Bernoulli's principle, while head losses in pipes are accounted for via the Hazen-Williams formula. Once the above model is formulated for a given water distribution network, the system can be simulated either in *demand-driven* mode, which, under normal conditions, assumes that the pressure in the system depends on node demands and, thus, the mass balance and head loss equations are solved assuming that node demands are known and satisfied, or in *pressure-driven* mode, which assumes that the delivered demand depends on the available pressure in the system and accounts for possible demand shortages. In emergency/anomaly situations (i.e., firefighting, power outages, pipe leaks), consumers do not always receive their requested demand in a pressure-driven scenario.

Several state-of-the-art software tools are available to model water distribution networks of various scales. Arguably, the most widely used among them is EPANET, developed as open-source software by the United States Environmental Protection Agency (Rossman et al., 2000). EPANET can perform also water quality simulation beside hydraulic simulations, thus allowing for coupled hydraulic and water quality simulation, which increases the size of the problem formulated in Equations (10) by adding states related to water quality parameters, along with the possibility of controlling it (e.g., via chlorine dosage). Yet, EPANET model implementations are not straightforward as control-oriented models, since they often include several switches and discrete operation conditions that make them not suitable for the direct application of gradient-based optimization approaches.

Alternative software tools exist to model other networks of the urban water cycle such as combined and sanitary sewers and other drainage systems, e.g., the US-EPA Storm Water Management Model (SWMM) (Rossman et al., 2010). A broad formulation of the system model as indicated in Equation (10) and overall modelling strategy still stands, with water flows being ruled by mass and energy conservation laws. However, individual system components to be modelled change, with disturbances to be forecasted being most typically rainfall and inflow to the system, and controls being basin outflows, gate settings, and, more on an infrastructure planning perspective, Low-Impact Development (LID) controls. Complementary tools such as the one reported in Riaño-Briceño et al. (2016) allow the use of SWMM to design control strategies, in particular, applied to drainage systems, with some flexibility and considering dynamical models and a more realistic setup including disturbances and their forecast models.

In some cases, e.g., for large-scale urban water networks, it is useful to replace the full model of the system with a reduced model of the network that can offer higher computational efficiency (Shamir and Salomons, 2008). This is usually done via skeletonization by reducing the number of components of the system (e.g., by removing irrelevant pipes and nodes) while retaining a high level of similarity between the reduced and full model outputs and performance. Alternative approaches instead rely on the development of data-driven surrogate models.

### *2.3. Literature Search and Classification Methods*

This section describes the search methods, keywords and criteria followed for the bibliographic search highlighting common points and workflows across water systems, as well as differences (e.g., keywords, etc.). Real-time control techniques applied to water systems take sometimes different names but can be reduced to an MPC-like approach as long as they embed the three main blocks of MPC (see Introduction): (i) the internal model of the system, used to simulate the effects of the control actions on the system, (ii) the use of forecasts available in real-time, either real, synthetic or 'perfect' forecasts and (iii) an online optimization that is reiterated over a receding horizon. In the water systems' literature, several studies have adopted an MPC-like technique either referring to it with different wordings, like 'rolling horizon control', 'receding horizon control', 'real-time optimization', or proposing some theoretical modifications to the MPC approach and providing an alternative name (e.g., Partial Open-loop Feedback Control). To account for such alternative wordings for "Model Predictive Control" and domain-specific differences, we formulated customized versions of the literature search string for each of the three water system types considered and used them to identify relevant papers in the Web of Science platform [3]. The resulting search strings are the following:

- For water reservoirs: (optimal AND water AND reservoir* AND (operation OR control OR management) AND (predictive control OR forecast-based OR receding horizon OR rolling horizon OR receding-horizon OR rolling-horizon))
- For water channels: (Model predictive control OR MPC OR receding horizon OR rolling horizon) AND (water canal* OR water channel* OR irrigation OR inland OR inland waterway*)
- For urban water networks: (optimal AND water AND (drinking OR distribution OR transport OR wastewater OR drainage OR grey water OR sewer OR sewage) AND (networks OR systems) AND (operation OR control OR management) AND (model predictive control OR predict* control OR naive feedback control OR receding horizon OR rolling horizon OR receding-horizon OR rolling-horizon))

The search queries are not restricted to the word 'Model Predictive Control', so the records found include some irrelevant studies. Exclusion criteria only regarded (i) article language (only papers written in English were considered) and (ii) and article type (only peer-reviewed publications in scientific journals were considered). Conference papers were excluded to avoid redundancies since some conference publications often present preliminary versions of studies subsequently published in full journal papers. We acknowledge that some of the most recent advanced developments, that might be present in a few recent peer-reviewed conference publications, may not have been covered in this review, but overall we do not expect that it would have a significant impact on the identified trends and challenges, given the large sample of journal articles included.

Manual filtering on the resulting records was performed based on paper title and abstract, to discard items that were out of scope for this review (i.e., not focusing on MPC or not applying it to the water systems of interest), before evaluating the eligibility of a restricted set of papers based on their full-text assessment. A smaller set of additional relevant papers not retrieved with the search query (7 items) was added to the final database from other sources, namely from references in previous review papers resulting from the search (see Figure 4 for details on the sample selection).

[3] https://www.webofscience.com/

## 3. Review Results

### 3.1. MPC for water reservoirs

In the last 15 years, several studies analyzed the potential of forecast-based real-time control techniques for water reservoir systems across different real-world problems by leveraging the increasing availability and improved quality of hydro-meteorological forecasts. The query formulated to retrieve peer-reviewed journal articles on MPC for water reservoir systems (see Section 2.3) returned an initial set of 105 papers. After screening these manuscripts, we retained 33 publications and added 7 more documents (from references in previous reviews on optimal control of reservoirs that were found by the query), yielding a total of 40 articles that have been analyzed in detail (see PRISMA diagram in Fig. 4). As recently highlighted in Giuliani et al. (2021), our review confirms that MPC approaches (and analogous approaches that could be reduced to MPC) have been applied more commonly only in recent years, with the 40 studies reviewed here that have been published from 2008 to 2022 (see the temporal distribution in Fig. 5).

Almost all reviewed papers implement a centralized control architecture to determine the optimal releases from one or more reservoirs, with only a few applications also dealing with the control of pumps (e.g., Galelli et al., 2014; Javan Salehi and Shourian, 2021). Most studies implement a daily controller (e.g., Wan et al., 2016; Anghileri et al., 2016), but we found applications working at either sub-hourly (e.g., Breckpot et al., 2013a; Lin et al., 2020) or hourly (e.g., Delgoda et al., 2013; Karimanzira et al., 2016; Xu et al., 2020) or monthly (e.g., Zambelli et al., 2011; Kistenmacher and Georgakakos, 2015) frequencies. Suppose the forecast frequency is not sufficient to timely inform the control action. In that case, the MPC results should be seen as a recommendation provided by a decision support system that the operator can adjust, potentially taking into account local expert knowledge and any operating factors that the MPC optimization could not cover (e.g., Roetz and Theobald, 2019).

In almost all the reviewed studies (see Table 1), the forecast represents the inflow to the reservoir, which is usually generated using a hydrological model fed by meteorological forecasts and any other significant information available at each control time step (e.g., snowpack and hydrological conditions, including the streamflow upstream, being routed using the model). Only two studies (Galelli et al., 2014, 2015) complement the inflow with tide forecasts. Moreover, many studies (more than half) use a deterministic forecast and MPC formulation (e.g., Giuliani and Castelletti,

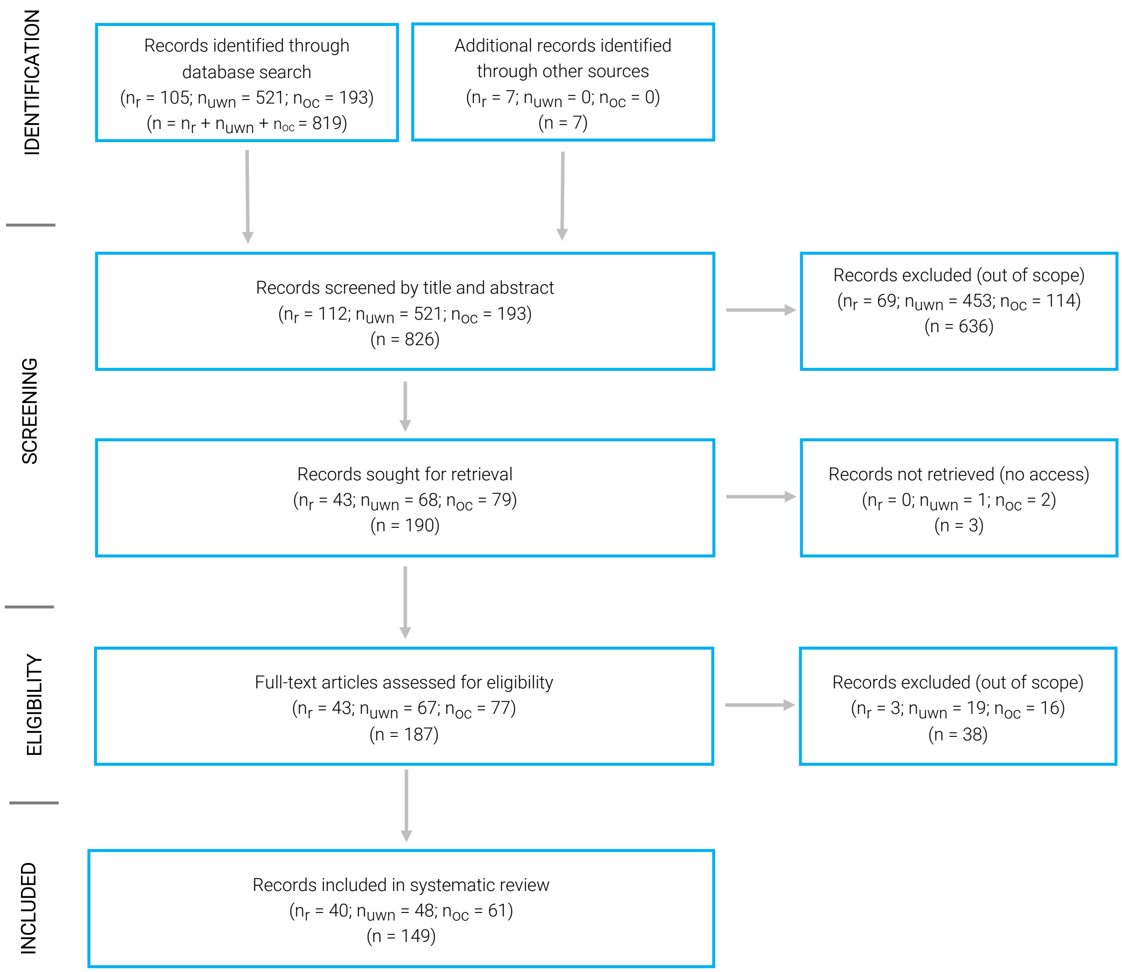


Figure 4: Flow diagram with paper exclusion/inclusion criteria. The flow diagram reports the exclusion/inclusion criteria applied to the dataset of papers retrieved for review, represented according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines (PRISMA; Moher et al., 2009). $n_r$ indicates the number of papers on MPC for water reservoirs, $n_{uwn}$ those on MPC for urban water networks, and $n_{oc}$ those on MPC for open channels. $n$ is the number of total papers (equal to the sum of the above, i.e., $n = n_r + n_{uwn} + n_{oc}$).

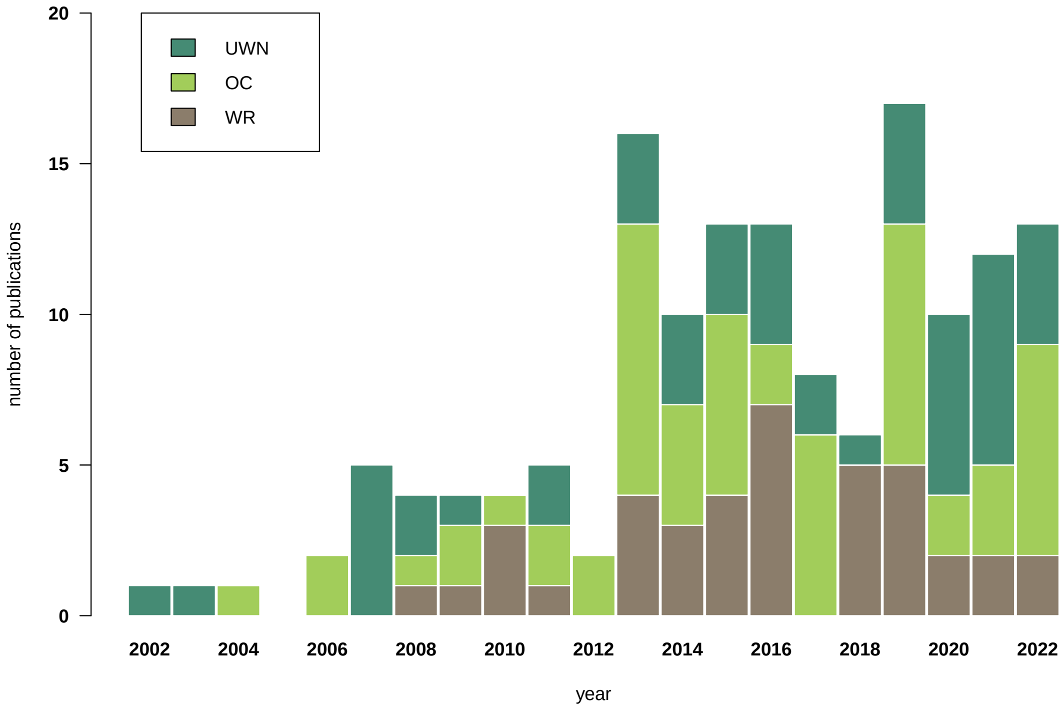


Figure 5: Annual counts of the 149 publications reviewed in this study by type of water system (WR: Water Reservoirs; OC: Open Channels; UWN: Urban Water Networks).

2013; Anand et al., 2013; Galelli et al., 2015), although the adoption of stochastic formulations is increasing in the last few years (e.g., Uysal et al., 2018b; Sahu and McLaughlin, 2018; Ahmad and Hussain, 2019). These stochastic approaches (see Section 2.1.2 and Table 2) allow the explicit probabilistic characterization of the forecast uncertainty by relying on ensemble forecasts and, therefore, better hedge against risk (Breckpot et al., 2013a).

The reviewed papers used a wide range of control time steps (see Table 3) and of forecast horizons (also called *lead times* in the forecasting literature) ranging from a few hours for responding to rapid events such as floods (e.g., Blanco et al., 2010; Galelli et al., 2014, 2015; Xu et al., 2020) to seasonal or longer scales (e.g., Xu et al., 2015; Anghileri et al., 2016; Raso and Malaterre, 2017; Gavahi et al., 2019). However, multiple timescales have never been incorporated into a seamless multi-timescale system in any case study.

Despite changes in societal perceptions of water resources generally enlarge the number of objectives considered (e.g., Giuliani et al., 2014a,b; Wild et al., 2019), a large majority of the studies we considered formulate a single-objective control problem (e.g., Wang, 2010; Breckpot et al., 2013a; Xu et al., 2015; Sahu and McLaughlin, 2018; Arsenault and Cote, 2019) or an a-priori aggregation of multiple objectives (e.g., Castelletti et al., 2008a; Kistenmacher and Georgakakos, 2015; Uysal et al., 2018a), with very few exceptions that consider either 2 or 3 competing objectives (e.g., Giuliani and Castelletti, 2013; Xu et al., 2020; Lin et al., 2020; Mohanavelu et al., 2022) (see Table 4). The scalability of MPC to multi- and many-objective control problems is indeed an important limitation for the application of this control strategy to water reservoir systems (Giuliani et al., 2021), which often has limited ability in exploring multi-dimensional trade-offs (e.g., Giuliani et al., 2016).

About half of the reviewed articles (see Table 4) provide a comparison between MPC against an alternative, off-line control strategy often designed via Stochastic Dynamic Programming (SDP) or against the current operational schemes of real-world reservoirs (e.g., Castelletti et al., 2008a; Xu et al., 2015; Sahu and McLaughlin, 2018). All these studies found that MPC outperforms other strategies. This is often attributed to the fact that MPC ensures that the control is adapting to extreme events that can be forecasted in the short- to long-term based on current observations and other forecast data (e.g., Galelli et al., 2014; Ficchi et al., 2016; Ahmad and Hussain, 2019). However, the choice of a reservoir control method is expected to depend upon multiple factors, including the system's characteristics, the objectives of the control, the specified constraints, data and forecast availability (Macian-Sorribes and Pulido-Velazquez, 2020). So large comparison studies are needed to investigate MPC's applicability, effectiveness, and value in different contexts.

Only a few studies benchmark MPC against multiple state-of-the-art control methods, such as different Approximate Dynamic Programming (ADP) methods (see Table 4)). Notably, Mohanavelu et al. (2022) compare six state-of-the-art control methods for the operation of a real-world reservoir system in India (i.e., the Pong reservoir). They found that MPC outperforms all the other methods, yielding the closest solution to the ideal one designed via Deterministic Dynamic Programming (DDP). A limitation of their study is that MPC was driven by a single forecast close to perfect forecasts, so further studies are needed to extend such comparisons for different case studies and use real forecasts with different levels of skill and timescales within the MPC. Similarly, Kergus et al. (2022) benchmark an MPC-based approach against SDP and the ideal DDP solution with perfect foresight for the operation of a reservoir in Vietnam (Hoa Binh). Their MPC-like approach (combining hierarchically MPC with an inner parametric data-driven feedback controller) uses statistical forecasts with a random noise added on the disturbances. Despite the error in the disturbance predictions, the MPC-based approach outperforms SDP by obtaining better trade-offs between the two objectives (hydropower and flood control) and approaches the ideal solution by DDP. However, as pointed out by Kergus et al. (2022), while these results are encouraging for MPC, the robustness to prediction errors requires further investigation. Likewise, other six studies (Castelletti et al., 2008a; Wang, 2010; Galelli et al., 2014; Sahu and McLaughlin, 2018; Ahmad and Hussain, 2019; Payet-Burin et al., 2021) benchmark MPC with SDP reaching similar conclusions. MPC approaches outperform the offline benchmark by better anticipating the inflow events, especially those out of their typical season, even if a simple inflow forecasting model is used (e.g., Castelletti et al., 2008a; Wang, 2010). MPC generally leads to better trade-offs between objectives, with the performance increasing with increased prediction horizon (e.g., Castelletti et al., 2008a; Galelli et al., 2014). MPC can also deal with problems that are computationally intractable by SDP due to the number of reservoirs in the system (e.g., Wang, 2010), as it overcomes the curses of dimensionality and modelling of SDP.

A limitation of the current body of literature on MPC for reservoir operation is that most studies do not assess the impact of the MPC internal model uncertainty, as usually the same models have been used for both the open-loop optimization and closed-loop simulation (with the associated update of model states) in almost all studies reviewed. A few exceptions exist (Munier et al., 2015;

Lin et al., 2020). For example, Lin et al. (2020) used two different models: a simplified internal model was used in the open-loop optimization, as is usually done in MPC, and a more refined and computationally-intensive model was employed to represent the real water system in closed-loop, to update water levels and flows.

### *3.2. MPC for open channels*

An initial set of 193 research journal papers was obtained using the query formulated in Section 2.3, of which only 58 were retained after the manual screening of titles and abstracts (see PRISMA diagram in Figure 4). Inspection of the time distribution of the final set of papers (depicted in Figure 5) reveals that all papers were published less than twenty years ago (and twenty-six of them less than five years ago), which allows identifying a growing interest in the topic (see Figure 5). It is also worth noting that other review papers were returned by the query: although not strictly research papers, they are surveyed for completeness. An exhaustive review of modelling and control of open-channel irrigation systems is carried out in Conde et al. (2021), and an entire section (Section 4.5.3) is devoted to MPC. Different applications of smart agriculture are presented in Ding et al. (2018), including the use of MPC for irrigation systems (Section 3.1). The developments of an industrial-scale project that culminated in the complete automation of a large irrigation system in Australia are discussed in Mareels et al. (2005). Although MPC approaches are not explicitly developed therein, the same research group has recently employed MPC to control a river (Foo et al., 2014) and an irrigation canal (Nasir et al., 2021).

Control of water canals and rivers aims to satisfy human needs, which are expressed in the form of a cost function. Most of the reviewed papers are characterized by cost functions built as the weighted sum of individual terms (i.e., the relative importance of each term is adjusted using weights), with the minimization of water level setpoint tracking errors and operational costs being the most common objectives (see Table 4). Additional goals, e.g., simultaneous control of water quantity and quality (Xu et al., 2013; Aydin et al., 2019, 2022), preservation of water levels within safe navigation bounds (Wagenpfeil et al., 2012; Tian et al., 2019; Segovia et al., 2019; Pour et al., 2022; Horvath et al., 2022) and pressure reduction for the pressurized part of the network (Zhu et al., 2020), are also considered in the literature. Moreover, Foo et al. (2014) tailor a cost function to the needs of their case study, e.g., maintain off-stream storage volume above a threshold, release as little water from a lake as possible and keep flows for early spring to mid-summer under a threshold to create slack-water pockets. On a wider note, joint water and energy management in water canals appears to be a topic of increasing interest in the water-energy nexus context (Doan et al., 2013; Pour et al., 2022; van der Heijden et al., 2022; Horvath et al., 2022).

Operational management of water canals is carried out by manipulating the available actuators. Inspection of the surveyed papers reveals the use of a wide variety of actuators, i.e., gates, weirs, sluices, pumping stations, dams, turbines and electro-valves (see Table 3). Control decisions are either actuator flow or position setpoints; an assessment of the optimal choice of the input variable is carried out in Horvath et al. (2015b). These decisions are computed over prediction horizons (the reviewed papers report values ranging from one minute to ten days), and are applied with fixed frequencies (ranging from once every five seconds to once every six hours) for the whole duration of the experiment (ranging from thirty minutes to one year). The effect of these decisions on the system is measured using available sensors that capture relevant information, e.g., water levels, salinity and concentration of chemical species. This information, together with estimates of unmeasurable states (obtained using observers), allows adjusting the decisions at the next time step. It is interesting to highlight the large variability in terms of time scales across reviewed papers (see Tables 1 and 3). These differences can be explained by the different nature of the experiments: real case studies, either on a real system (Foo et al., 2014; Nasir et al., 2021) or in silico (Romera et al., 2013; Tian et al., 2017a; Kong et al., 2019b), laboratory canals (Lemos et al., 2009; Figueiredo et al., 2013; van Overloop et al., 2014; Horvath et al., 2015b,a; Aydin et al., 2017), canal benchmarks (Wahlin, 2004; Wahlin and Clemmens, 2006b; Rodriguez et al., 2020) and academic examples (Xu et al., 2011, 2012, 2013; Breckpot et al., 2013b; Xu and Schwanenberg, 2017) are reported. In particular, laboratory canals are characterized by reduced dimensions in comparison to the rest of the case studies, which explains the use of smaller time scales.

It was discussed in Section 2.1 that MPC is a model-based approach and that, as such, an internal model is required to predict the effect of control actions on the system. Existing open-channel internal models have been presented in Section 2.2.2. On the one hand, some of the employed models are directly derived from the Saint-Venant equations, e.g., discretizing the system in space and linearizing (Wagenpfeil et al., 2012; Xu et al., 2012; Tian et al., 2015; Aydin et al., 2019, 2022). On the other hand, other papers resort to the integrator delay (Hashemy Shahdany et al., 2017; Zheng et al., 2019; Kong et al., 2019b; Rodriguez et al., 2020; Avargani et al., 2022; Askari Fard et al., 2022; Liu et al., 2023), the integrator delay zero (Romera et al., 2013; Segovia et al., 2019; Pour et al., 2022) and the integrator resonance (van Overloop et al., 2014; Horvath et al., 2015a,b) models. While a large variety of models is employed in the reviewed papers, it can be concluded that the use of the ID model is prevalent (in its equivalent state-space form). Finally, a model-free strategy is proposed by Ren et al. (2021), whereby control policies are obtained via deep reinforcement learning.

The performance of MPC is also affected by disturbances. Water canals are operated under time-varying environmental conditions, which are exogenous inputs that attenuate the effect of control actions and thus complicate the attainment of the operational objectives. Therefore, the occurrence of these events may have a severe effect on water levels unless properly accounted for in the MPC design. Although the type of disturbance considered depends on the case study, uncontrolled in- and/or outflow forecasts, e.g., rainfall (van Overloop et al., 2008; Negenborn et al., 2009; Xu et al., 2011; Maestre et al., 2013; Velarde et al., 2019), surface-groundwater interaction (Foo et al., 2014; Aydin et al., 2019) and sea discharges (van Ekeren et al., 2013; Tian et al., 2015; van der Heijden et al., 2022), are typically used (see Table 1). In addition to these, operational disturbances, e.g., offtake flows for irrigation purposes (Wahlin, 2004; Wahlin and Clemmens, 2006a,b; van Overloop et al., 2010a; Breckpot et al., 2013b; Hashemy et al., 2013; Shahdany et al., 2015; van Overloop et al., 2015; Shahdany et al., 2016; Xu, 2017; Zheng et al., 2019; Kong et al., 2019a; Shahdany et al., 2019; Kong et al., 2021), wind effect (Wagenpfeil et al., 2012) and lock operations for navigation purposes (Segovia et al., 2019; Pour et al., 2022), are also considered. While either perfect or no knowledge about operational demands is usually considered (scheduled and unscheduled operations, respectively), uncertain meteorological conditions have motivated the development of stochastic MPC approaches for water canals (van Overloop et al., 2008; Maestre et al., 2013; Tian et al., 2017b, 2019; Velarde et al., 2019; Nasir et al., 2021), whereby different disturbance realizations with individual occurrence probabilities are considered (see Table 2).

In terms of the architecture of controllers for water canals, given the characteristics of centralized/distributed controllers (as introduced in Section 2.1), distributed control architectures appear to be preferable to overcome the computational and scalability drawbacks arising from centralized implementations. However, only eight papers consider distributed architectures (see Table 3), of which four are characterized by a two-layer structure in which the top layer takes care of the high-level problem setup: uncertainty realization (Velarde et al., 2019), reduction of communication overhead among local controllers (Farhadi and Khodabandehlou, 2016), selection of optimal network topology (Fele et al., 2014) and execution of risk mitigation actions (Zafra-Cabeza et al., 2011). The remaining four papers consider distributed single-level architectures (Negenborn et al., 2009; Maestre et al., 2013; Alvarez et al., 2013; Doan et al., 2013). The reduced number of papers that employ distributed multi-level architectures may be explained by the fact that the choice of control architecture depends mostly on the extent to which systems are coupled, communication reliability and computational resource availability. Canals have been traditionally regulated either manually or using decentralized proportional-integral (PI) controllers that adjust the setpoints dictated by a centralized coordinator (Sadowska et al., 2014, 2015; Nasir et al., 2021), which means that coupling effects might not be too relevant for their usual operation.

The benchmarking of MPC performance against other approaches is rarely included in the literature on open-channel control, as shown in Table 4. MPC is only compared to other two control approaches, namely LQR (Liu et al., 2023; Zheng et al., 2019; Kong et al., 2019a; van Overloop et al., 2010a; Wahlin and Clemmens, 2006a) and PI(D) (Liu et al., 2023; Kong et al., 2019a; Foo et al., 2014; van Overloop et al., 2015; Figueiredo et al., 2013; Lemos et al., 2009; van Overloop et al., 2008; Wahlin and Clemmens, 2006b; Wahlin, 2004), whereby the superior performance of MPC is demonstrated. Furthermore, although not explicitly reported in Table 4, benchmarking MPC against manual control demonstrates that MPC leads to better performance and thus improved system operation (Foo et al., 2014; Askari Fard et al., 2022).

As a final remark, not all papers report information regarding, e.g., nature of the forecast, system size (number of states), prediction horizon, frequency of decisions and optimization method, in an explicit manner. This fact complicates the analysis of the reviewed references.

### *3.3. MPC for urban water networks*

The query to retrieve peer-reviewed journal articles on MPC developments and applications to control urban water networks (see Section 2.3) returned an initial set of 521 papers. From this set of papers, 453 were excluded from further analysis after manually screening each paper's title and abstract, and 19 more based on relevance and fit within the scope of this review (see PRISMA diagram in Fig. 4). As a result, a subset of 48 articles was retained for detailed tagging and classification. This group of 48 papers corresponds to 9.4% of the initial dataset of papers retrieved with the formulated query. Many of the excluded papers were initially obtained as a result of the search query because they include the keywords listed in the search query in their main text or other parts. However, they were then deemed not relevant in relation to the scope of this review primarily either because of their actual MPC implementation (they only mentioned MPC or other control schemes but eventually only focused on model development), or because of their spatial scale of interest. Many studies indeed mentioned urban water systems and networks but eventually focused only on optimal control of processes occurring in individual network components (e.g., water treatment plants). For the above reasons, many papers initially identified in the search were assessed as not eligible for consideration in this review. The time distribution of these 48 articles shows that the last 25 years have witnessed an increasing interest towards the implementation of MPC schemes to control urban water networks. Likely motivated by the increasing amount of (quasi) real-time sensor data from distributed infrastructure networks, which act as enablers of real-time control schemes (Creaco et al., 2019), more than 45% of the reviewed studies ($n = 22$) were published in the last 5 years only (see Figure 5).

Integrated urban water management requires optimal planning and operations of different network systems which make up the urban water cycle, including drinking water networks, stormwater, greywater, and wastewater networks. Accordingly, examples of MPC developments and applications emerge from the literature for supply-side management of drinking water networks and stormwater and wastewater management. In addition, other recent publications reviewed the existing literature on control schemes for urban water networks. Yet their scope is rather constrained to only one type of network infrastructure, i.e., sewer systems (Van Der Werf et al., 2022) or water supply and distribution networks (Coelho and Andrade-Campos, 2014), and various control schemes are considered. Conversely, the scope of this review is only spatially constrained by the boundaries of the integrated urban water system and thematically by the focus on MPC-like control. Still, it is inclusive of all its sub-components. This review thus compares MPC studies focused on drinking water networks, as well as wastewater and sewage networks, to identify the type of disturbances, objectives, actuators, and type of MPC in each case, ultimately evaluating the benefits brought by MPC and its related challenges.

Most of the reviewed papers address the problem of optimal control of water distribution and transport networks ($n = 34$). The typical research goal in these works is to identify optimal operations of pumps and valves, i.e., the actuators distributed in a water distribution/transport network. The number of actuators in network infrastructure systems depends on the considered network's topological and structural characteristics and size. Their number affects the number of control variables in the optimal control problem. In our compilation of reviewed papers (see Table 3), control variables vary from less than 10 in simplified or small systems (e.g., Sankar et al., 2015; Salomons and Housh, 2020) to more than 120 in larger, real-world systems (Ocampo-Martinez et al., 2011). Water distribution systems are operated under varying water demand conditions. Forecasts of water demand are thus needed as input to the underlying hydraulic or data-driven models used in MPC. Water demand forecasts usually span over a period of 24 hours, relying on the day/night periodicity of water demand patterns, whereas the frequency of decisions is in the range of a few minutes (e.g., 5 minutes as in Liu et al. (2020)) and 1 hour (Wang et al., 2016, 2020). Controls in water transport and distribution networks are computed in such a way that an economic objective accounting for the cost of running the system (mainly due to electricity consumption for water pumping and pump start-up costs) is minimised, while water demands in the system are satisfied (e.g., Shamir and Salomons, 2008). Additional objectives such as guaranteeing safety storage in water tanks, pressure control, or smoothness of the controls are also often weighted in the complete objective function (e.g., Ocampo-Martinez et al., 2012; Wang et al., 2017; Grosso et al., 2014; Grosso Pérez et al., 2016). Only a recent paper on optimal reconfigurations of large-scale systems via backup actuator activation formulated a multi-objective mixed-integer programming (MIP) problem with two separate objectives (see Table 3), which was then solved with a lexicographic approach (Trapiello et al., 2021). A minority of works also considers water quality objectives, typically quantified via chlorine concentration in the supplied water (Biscos et al., 2003; Muslim et al., 2008).

The remaining 14 papers deal with optimal management of sewer and drainage infrastructure, where pumps and gates should be controlled to guarantee cost-effective and smooth operations, reduced peak flow to wastewater treatment plants, flood control, and avoid overflow in combined systems (CSOs; Darsono and Labadie, 2007; Puig et al., 2009; El Ghazouli et al., 2022). Rainfall is usually the uncertain variable to be forecasted (see Table 1) usually with a sub-hourly prediction horizon (e.g., 30 mins in Joseph-Duran et al., 2014; Sun et al., 2020), which provides information on the expected inflow to the system to design optimal decisions of gates to be applied with an operational frequency of 1-5 minutes (Marinaki et al., 1999; Sun et al., 2020; Joseph-Duran et al., 2015, 2014) to a few hours or a day (Dong and Yang, 2019).

Further, a limited yet recently growing number of articles develops control schemes based on MPC to operate pumps as turbines and harness the excess energy that would be otherwise dissipated for electricity production (Venturini et al., 2017; Stefanizzi et al., 2020; Levieux et al., 2021; Pirard et al., 2022). While they are not included in this review because they are not directly concerned with the optimal management of water resources, it is worth mentioning them as recent literature is shaping around joint opportunities for water and energy management within the broader context of the water-energy nexus.

The reviewed papers present a variety of applications and case studies, with different formulations of the objective function, controls, disturbances and forecasting horizon, system characteristics, and overall goals. Hence, results are also often case-specific and hard to generalise. However, in most reviewed works, MPC schemes - primarily implemented with a centralised architecture - are benchmarked against other control strategies and comparatively attain a better performance (i.e., reduced operational costs and violation of physical and operational constraints). Historical/current rule-based controls are usually taken as baseline reference (e.g., in Wang et al., 2020; Balla et al., 2022), along with local controllers (Puig et al., 2009) and PI controllers (Martin et al., 2022). A solid alternative for either implementing non-centralised control approaches or complementing control strategies for the management of UWNs is based on evolutionary game theory (Quijano et al., 2017). For the former case, several proposals have been reported towards not only designing predictive controllers accounting for the suitable partitioning of a large-scale drinking water network (Barreiro-Gomez et al., 2019; Muros et al., 2018) but also the synthesis of control strategies entirely based on such game theory (Barreiro-Gomez et al., 2016, 2017b; Obando et al., 2022). Regarding game-theory-based approaches that assist a predictive controller, tuning methodologies for multi-objective predictive controllers are also reported (Barreiro-Gomez et al., 2017a).

Overall, MPC has proven to be effective in attaining substantial cost savings in comparison to existing rule-based or set-point controllers in water distribution networks, which usually operate based on storage level thresholds. For instance, energy cost savings between 8% and 10% were calculated with simulations for a summer and winter month in Shamir and Salomons (2008). Other studies considering MPC controllers in urban drainage networks found that MPC can reduce the number of flooded nodes during an extreme weather event and lower peak flow by more than 50% in drainage systems subject to heavy rainfall events (Shishegar et al., 2021; Kändler et al., 2022). Case-specific results and cost/energy savings referred to different baseline values, implementations of the objective functions, and MPC parameters, though, do not allow for a direct quantitative comparison of MPC performance across studies. Further, several limitations and existing research gaps emerge from the analysis of the 48 reviewed papers. Most of the considered studies adopt, at least to some extent, a series of simplifications to address the challenges related to (i) accounting for uncertainties in disturbance prediction and (ii) dealing with the computational burden of simulating potentially large real-world networks in model-based approaches.

Concerning the first group of challenges, only six studies out of 48 consider the uncertainty in disturbance forecasts by implementing a stochastic or combined deterministic and stochastic MPC approach. The majority instead focuses on demonstrating the superiority of MPC in comparison to other control strategies under a deterministic scenario. This scenario is sometimes built assuming perfect disturbance prediction (Marinaki et al., 1999; Tedesco et al., 2016) or simple statistics on water demands from past data, while the type of forecast remains unclear in many other cases.

Concerning the second group of challenges, reducing the computational effort required to simulate large real-world networks is addressed in the literature with three different types of simplification approaches. First, some studies only consider very small networks, usually built ad hoc as artificial systems for research purposes, composed of a handful of nodes and just a few actuators (Sankar et al., 2015). This approach also makes up for the lack of data that often limits the possibility of developing studies based on real-world urban water networks. Other studies instead simplify the size of existing real-world systems by removing irrelevant nodes and links and obtaining a *skeletonised* system (as, for instance, in Shamir and Salomons, 2008). Beside the physical properties of the considered system, its operational properties and the physical characteristics of its actuators are often simplified, too. For example, some work only consider fixed-speed pumps, simple valve models characterised only by upper and lower bounds on the flow, and none consider dynamic/time-varying energy prices, but a few exceptions. Our review found that 27 studies are based on simplified or synthetic case studies, while only 10 rely on full-scale real-world systems. A third strategy to deal with the computational effort required by the simulation of large-scale hydraulic networks is the implementation of data-driven surrogate (or meta) models that substitute the high-fidelity hydraulic model with more computationally efficient yet still accurate models that can be coupled with optimisation. Dong and Yang (2019), for instance, implement a long-short-term memory (LSTM) neural network for operation scheduling of water diversion and drainage pumping stations in the presence of complex hydrometeorological constraints. Many research efforts have been recently developed revolving around surrogate models, also pushed by recent development in artificial neural networks and deep learning (e.g., Fiedler et al., 2020). As many are pretty recent

Table 1: Summary of the disturbances and forecast features of the studies reviewed applying MPC to water systems, grouped by type of system (WR: Water Reservoirs; OC: Open Channels; UWN: Urban Water Networks). Numbers indicate the frequency for each class, with citations for rare features in the literature (up to 3 articles) to highlight the studies with peculiar or unique features.

| **DISTURBANCE AND FORECAST FEATURES** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **FORECASTED VARIABLE** | | **Rainfall / inflow** | **Tide** | **Water demand** | **Electricity demand** | **Lock operations** | **Concentrations of chemical species** | **Wind** | **Head / water levels** |
| | WR | 40 | 2 (Galelli et al. (2014,2015)) | 0 | 0 | 0 | 0 | 0 | 0 |
| | OC | 22 | 3 (van Ekeren et al. (2013), Tian et al. (2015), Pour et al. (2022)) | 33 | 1 (van der Heijden et al. (2022)) | 2 (Wagenpfeil et al. (2012), Segovia et al. (2019)) | 3 (Xu et al. (2013), Aydin et al. (2019), Aydin et al. (2022)) | 1 (Wagenpfeil et al. (2012)) | 0 |
| | UWN | 6 | 0 | 24 | 0 | 0 | 1 (Dong and Yang (2019)) | 0 | 2 (Dong and Yang (2019), Kändler et al. (2022)) |
| **FORECAST TYPE (PERFECT/REAL)** | | **Perfect** | | **Statistical or ML-based (including synthetic)** | **Process-based** | **Hybrid (process-based + statistical/ML))** | | **Complete lack of knowledge** | **Unclear** |
| | **WR** | 15 | | 21 | 16 | 2 (Ahmad and Hossain (2019), Wei and Xun (2019)) | | 0 | 4 |
| | **OC** | 35 | | 6 | 5 | 1 (van Overloop et al. (2008)) | | 13 | 9 |
| | **UWN** | 2 (Marinaki et al. (1999), Tedesco et al. (2016)) | | 8 | 1 (Shishegar et al. (2021)) | 0 | | 0 | 37 |
| **PREDICTION HORIZON** | | **$\leq$ 1 hour** | **$\leq$ 1 day** | **$\leq$ 1 week** | | **$\leq$ 1 month** | **$\leq$ 1 year** | **$>$ 1 year** | **Unclear** |
| | **WR** | 0 | 5 | 12 | | 9 | 7 | 4 | 3 |
| | **OC** | 10 | 34 | 5 | | 1 (Tian et al.(2015)) | 0 | 0 | 9 |
| | **UWN** | 6 | 28 | 2 (Salomons and Housh (2020), Shishegar et al. (2021)) | | 0 | 0 | 0 | 13 |

and only appear so far in conference proceedings, they might not have been captured by our review.

Finally, it must be noted that, while it was possible to identify the above trends and challenges, one non-negligible finding is that many works do not report sufficient details on the type of forecasts, system size (state variables), implemented optimisation method, benchmark, and in some cases even the formulation of the objective function. This limits our capabilities to carry out a complete analysis of the attributes of such studies and, in general, hampers their full reproducibility.

## 4. Discussion

While the three types of water systems considered (water reservoirs, open channels and urban water networks) feature domain-specific physical characteristics and different types of actuators,

Table 2: Summary of the disturbances representation (deterministic and stochastic approaches, uncertainty model) of the studies reviewed applying MPC to water systems, grouped by type of system (WR: Water Reservoirs; OC: Open Channels; UWN: Urban Water Networks). Numbers indicate the frequency for each class, with citations for rare features in the literature (up to 3 articles) to highlight the studies with peculiar or unique features. Note: if the ensemble is reduced, the reduced ensemble size is reported, as the one used in the optimization problem.

| **DISTURBANCE AND UNCERTAINTY REPRESENTATION** | | | | | |
|---|---|---|---|---|---|
| **DETERMINISTIC/ STOCHASTIC** | | **Deterministic** | **Stochastic** | **Both (Stochastic / Deterministic)** | |
| | **WR** | 23 | 13 | 4 | |
| | **OC** | 52 | 4 | 2 (Maestre et al. (2013), Tian et al. (2017b)) | |
| | **UWN** | 36 | 5 | 1 (Pedrosa et al. (2022)) | |
| **TYPE OF STOCHASTIC APPROACH AND ENSEMBLE SIZE** | | **ENSEMBLE** | | | **PDF** |
| | | $\leq$ **10** | $\leq$ **30** | $>$ **30** | |
| | **WR** | 3 (Delgoda et al. (2013), Ficchì et al. (2016), Payet-Burin et al. (2021)) | 8 | 2 (Anghileri et al. (2016), Uysal et al. (2018)) | 4 |
| | **OC** | 2 (van Overloop et al. (2008), Maestre et al. (2013)) | 3 (Tian et al. (2017b), Tian et al. (2019), Velarde et al. (2019)) | 1 (Nasir et al. (2019)) | 0 |
| | **UWN** | 2 (Grosso et al. (2014), Grosso et al. (2016)) | 0 | 1 (Grosso et al. (2017)) | 2 (Pour et al. (2020), Pedrosa et al. (2022)) |
| **OPERATOR OVER ENSEMBLE (IMPLICIT) OR PDF (EXPLICIT)** | | **IMPLICIT** | | | **EXPLICIT** |
| | | **Expected value** | **Tree** | **Min-max or quartiles** | **Expected value (PDF)** |
| | **WR** | 8 | 4 | 3 (Cuvelier et al. (2018), Ahmad and Hossain (2019), Arsenault and Cote (2019)) | 2 (Pianosi and Soncini-Sessa (2009), Wang (2010)) |
| | **OC** | 3 (van Overloop et al. (2008), Tian et al. (2019), Nasir et al. (2021)) | 3 (Maestre et al. (2013), Tian et al. (2017b), Velarde et al. (2019)) | 0 | 0 |
| | **UWN** | 2 (Grosso et al. (2014), Grosso et al. (2016)) | 1 (Grosso et al. (2017)) | 0 | 2 (Pour et al. (2020), Pedrosa et al. (2022)) |

Table 3: Summary of the control variable characteristics of the studies reviewed applying MPC to water systems, grouped by type of system (WR: Water Reservoirs; OC: Open Channels; UWN: Urban Water Networks). Numbers indicate the frequency for each class, with citations for rare features in the literature (up to 3 articles) to highlight the studies with peculiar or unique features.

| **CONTROL-RELATED INFORMATION** | | | | | | | |
|---|---|---|---|---|---|---|---|
| **FREQUENCY OF CONTROL ACTIONS** | | $\leq 1$ **hour** | $\leq 1$ **day** | $\leq 1$ **month** | $\leq 1$ **year** | $> 1$ **year** | **Unclear** |
| | **WR** | 11 | 18 | 9 | 1 (Xu et al. (2015)) | 0 | 1 |
| | **OC** | 51 | 3 (Foo et al. (2014), Tian et al. (2015,2017b)) | 0 | 0 | 0 | 4 |
| | **UWN** | 32 | 2 (Dong and Yang (2019), Shishegar et al. (2021)) | 0 | 0 | 0 | 15 |
| **NUMBER OF CONTROL ACTIONS** | | **1** | $\leq$ **5** | $\leq$ **10** | $\leq$ **50** | $>$ **50** | **Unclear** |
| | **WR** | 20 | 11 | 3 (Wang (2010), Kistenmacher and Georgakakos (2015), Karimanzira et al. (2016)) | 4 | 1 (Zmijewski et al. (2016)) | 1 |
| | **OC** | 8 | 21 | 10 | 16 | 0 | 3 |
| | **UWN** | 1 (Kändler et al. (2021)) | 9 | 10 | 6 | 10 | 0 |
| **TYPE OF CONTROL ACTION** | | **Reservoir release** | **Pump/valve operations** | **Gate operations** | **Chemical dosage** | **Other** | **Unclear** |
| | **WR** | 39 | 4 | 4 | 0 | 3 (Galelli et al. (2014,2015), Gavahi et al. (2019)) | 0 |
| | **OC** | 1 (Foo et al. (2014)) | 14 | 38 | 0 | 6 | 13 |
| | **UWN** | 1 (Marinaki et al. (1999)) | 34 | 6 | 0 | 2 (Shishegar et al. (2021), van der Werf et al. (2021)) | 5 |
| **CONTROL ARCHITECTURE (CENTRALIZED/ DECENTRALIZED/ DISTRIBUTED, SINGLE-LEVEL/ MULTI-LEVEL)** | | **Centralized, single-level** | **Centralized, multi-level** | **Decentralized, single-level** | **Decentralized, multi-level** | **Distributed, single-level** | **Distributed, multi-level** |
| | **WR** | 40 | 0 | 2 (Giuliani and Castelletti (2013), Anand et al. (2013)) | 2 (Giuliani and Castelletti (2013), Anand et al. (2013)) | 0 | 0 |
| | **OC** | 46 | 1 (Pour et al. (2022)) | 0 | 3 (Sadowska et al. (2014,2015), Nasir et al. (2021)) | 4 | 4 |
| | **UWN** | 35 | 0 | 1 (Martin et al. (2022)) | 1 (Wang et al. (2017)) | 0 | 0 |

Table 4: Summary of the problem size (state variables), objectives (number and type), and benchmarking of the studies reviewed applying MPC to water systems, grouped by type of system (WR: Water Reservoirs; OC: Open Channels; UWN: Urban Water Networks). Numbers indicate the frequency for each class, with citations for rare features in the literature (up to 3 articles) to highlight the studies with peculiar or unique features.

| **SYSTEM SIZE, OBJECTIVES AND BENCHMARKING** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **NUMBER OF STATE VARIABLES** | | **≤ 5** | **≤ 10** | | **≤ 50** | | **> 50** | **Unclear** |
| | **WR** | 30 | 3 (Wang (2010), Kistenmacher and Georgakakos (2015), Karimanzira et al. (2016) ) | | 3 (Myo Lin et al. (2018,2020), Salehi and Shourian (2021)) | | 1 (Blanco et al. (2010)) | 3 |
| | **OC** | 18 | 9 | | 18 | | 9 | 4 |
| | **UWN** | 8 | 4 | | 9 | | 3 (Marinaki et al. (1999), Grosso et al. (2016), Tedesco et al. (2016)) | 0 |
| **NUMBER OF OBJECTIVES** | | **1** | **≤ 4** | | **> 4** | | | **Unclear** |
| | **WR** | 35 | 5 | | 0 | | | 0 |
| | **OC** | 0 | 56 | | 2 (Foo et al. (2014), Pour et al. (2022)) | | | 0 |
| | **UWN** | 37 | 2 | | 0 | | | 10 |
| **OBJECTIVE TYPE** | | **Economic (cost minimization)** | **Flood/ overflow minimization/ water level control** | **Water supply/ demand satisfaction** | **Active actuator minimization/ smooth operations** | **Contaminant/ salinity concentration minimization** | **Environmental protection (environmental flow)** | **Hydropower** |
| | **WR** | 8 | 25 | 18 | 2 (Karimanzira et al. (2016), Uysal et al. (2018a)) | 1 (Galelli et al. (2015)) | 4 | 17 |
| | **OC** | 8 | 55 | 2 (Foo et al. (2014), Horvath et al. (2022)) | 47 | 2 (Aydin et al. (2019,2022)) | 2 (Foo et al. (2014), Horvath et al. (2022)) | 1 (Doan et al. (2013)) |
| | **UWN** | 11 | 8 | 0 | 11 | 3 (Biscos et al. (2003), Muslim et al. (2008), Cong Cong et al. (2016)) | 0 | 0 |
| **BENCHMARK** | | **DDP (Deterministic Dynamic Programming)** | **SDP (Stochastic Dynamic Programming)** | **Historical operation or current curves** | **PI control** | | **LQR** | **No benchmark/ unclear** |
| | **WR** | 4 | 8 | 11 | 0 | | 0 | 19 |
| | **OC** | 0 | 0 | 2 (Foo et al. (2014), Askari Fard et al. (2022)) | 6 | | 5 | 46 |
| | **UWN** | 0 | 0 | 10 | 2 (Muslim et al. (2008), Martin et al. (2022)) | | 0 | 35 |

objectives, and disturbances that should be accounted for in a control problem, common advantages/drawbacks of MPC, trends and challenges emerge from this review.

MPC offers three primary advantages over more conventional SDP and ADP methods: (A1) MPC overcomes the so-called 'curse of dimensionality' of Dynamic Programming, as it avoids the computation of the value function, by iterating the optimal control problem over a finite receding horizon; as a result, the computation costs of MPC do not increase exponentially with problem size (i.e., state and control dimension), which makes MPC a more viable approach for large-scale multi-reservoir systems with more than three reservoirs (e.g., Wang, 2010; Kistenmacher and Georgakakos, 2015; Ficchi et al., 2016), as well as for large OC (e.g., Shahdany et al., 2019; Rodriguez et al., 2020; Kong et al., 2021) and UWN (e.g., Martínez et al., 2007; Tedesco et al., 2016; Wang et al., 2021). (A2) MPC overcomes the 'curse of modeling' of DP by allowing the optimization model to take updated decisions at each time step with a real-time receding horizon strategy, making use of existing models and optimization frameworks (e.g., Segovia et al., 2019; Nasir et al., 2021; Mohanavelu et al., 2022). (A3) MPC can deal with hydro-climatic variability, nonstationarities and uncertainty (e.g., Castelletti et al., 2008a; Maestre et al., 2013; Velarde et al., 2019; Payet-Burin et al., 2021). By using real-time information and probabilistic forecasts in the optimization process, MPC allows water systems operation to adapt to changes in the climate or catchment and to mitigate the impacts of extreme hydrological events anticipating them, particularly those occurring in unusual periods of the year (e.g., Castelletti et al., 2008a). These advantages make MPC a more effective control technique and more feasible than DP for large water systems (especially large channel and urban water networks), as shown in a few studies benchmarking MPC against DP/ADP methods.

Although MPC has these advantages over more conventional DP and off-line methods, it also has a few drawbacks: (D1) The iterative optimization involved in MPC can also lead to intensive computations, especially for large-scale water systems with many actuators and a centralized controller. For example, for open channels, Ren et al. (2021) discuss how the computation burden associated with MPC can be a significant obstacle in large-scale systems with high-dimensional state and control spaces, making it impractical to perform online calculations at each time step; they call this a 'curse of dimensionality' for MPC too, though this is less prohibitive than for DP. Other authors have also paid attention to the trade-off between solution optimality and computation time, and have tested different MPC formulations to verify conditions under which optimal control actions may be determined within a prescribed real-time control period. For instance, Xu et al. (2012) test quadratic-programming-based (QP) and sequential-quadratic-programming-based (SQP) MPC, and find out that SQP-MPC achieves better control performance than QP-MPC at the expense of highly increased computation times (execution is  30 times slower). Alternative approaches to overcome the costs related to centralized MPC controllers applied to large-scale systems and to foster scalability have been explored also in urban water networks. Tedesco et al. (2016), for instance, test the use of distributed approaches (command governor strategies), in which the global control system is decomposed and local controllers are used, each responsible for the supervision of each subsystem. (D2) The performance of MPC is highly dependent on reliable prediction models, which may not be available for large-scale systems over long prediction horizons, making MPC-based control approaches ineffective in some cases (e.g., Ren et al., 2021).

Two main common trends can be identified: (T1) an increasing number of studies adopting ML-based models to predict the disturbances (e.g., inflows, tides); (T2) an expanding proportion of stochastic MPC applications over the last decade (since 2013), though still a minority to deterministic MPC.

The main challenges currently limiting the scope of MPC studies can be grouped into the following four categories, which should serve as main goals to formulate a research agenda for the next few years: (C1) lack of benchmarking studies that comprehensively compare MPC against other control schemes and assess its performance in relation to the characteristics of the physical system; (C2) lack of assessment of the uncertainty embedded in the model-based control and simplifications adopted in the model structure; (C3) incomplete analysis on the impact of the type of forecast, forecast resolution, and length of the prediction horizon; and (C4) limited exploration of tradeoffs and truly multi-objective MPC problems, to go beyond the single-objective nature of the problem formulation (that is often achieved via aggregation of multiple objectives functions appearing in multi-objective problems).

Related to the first challenge (C1) of evaluating the performance of MPC comprehensively and objectively, in most of the reviewed studies, there is a lack of consistent benchmarking of MPC with respect to other control methods and across systems with different characteristics. Only a few studies compare MPC against multiple alternative techniques, and none compare MPC with off-line alternatives using available forecasts in real-world settings. Most past studies across all types of considered water systems either used only perfect forecasts to set the upper-bound performance used as “ideal” reference (e.g., Uysal et al., 2018a; Marinaki et al., 1999), or focused on an off-line benchmark control scheme without actual forecasts, but rather with historical operations, typically based on rule curves or other set-point approaches (e.g., Delgoda et al., 2013; Xu et al., 2015; Wang et al., 2020) and Stochastic Dynamic Programming (e.g., Wang, 2010; Galelli et al., 2014; Kergus et al., 2022). A comparative analysis of the MPC performance in different contexts and in relation to case-specific characteristics (e.g., physical features of the system, constraints, objectives, etc.) would be important to assess the dependence between such characteristics and expected MPC results. However, many different factors are varying across the reviewed studies and for different types of systems, both in terms of system characteristics and optimization problem parameters. Thus, a direct comparison of existing quantitative results would not be meaningful. A fair comparative analysis would instead require consistent benchmarking studies comparing the relative performance of MPC with respect to the same benchmark control method across studies. We acknowledge that the performance of MPC can be affected by the characteristics of the basin, hydrology of the open channels, and other factors, which can vary significantly between different geographic regions. Therefore, further studies carrying out comparative analyses of MPC with consistent settings and with real-world data (beside synthetic cases, which are frequent in the reviewed papers) should be considered for water reservoirs, urban water networks, and open channels.

As for C2, the key element of MPC is the use of a model of the system to be controlled, yet models are always subject to errors, inaccuracies, and uncertainties. MPC leverages the accuracy of the models of the systems to ensure the robustness of the controller with respect to uncertainties (e.g., Schwenzer et al., 2021). Many studies reviewed recognise this aspect and provide at least some insights into the accuracy of the chosen internal models, supporting their choice (e.g., Galelli et al., 2014; Munier et al., 2015; Ficchi et al., 2016; Giuliani and Castelletti, 2013). However, some studies do not analyse the model’s accuracy in sufficient detail, and few do not provide any information on this. Moreover, most of the studies reviewed (more than 100 out of 149) do not assess the impact of the MPC internal model uncertainty as usually the same models for both the open-loop optimisation and closed-loop simulation (with an associated update of model states) have been used. This is especially the case for water reservoirs and urban water networks. Only for open channels, most of the studies ($>30$ out of 58, with few studies with unclear information) test MPC with a different internal prediction model than the model used for the closed-loop simulation. Simplified versions of the Saint-Venant equations are usually used as an internal model in the MPC, while the full Saint-

Venant equations, implemented in software solutions such as SOBEK (e.g., Wahlin and Clemmens, 2006b; van Overloop et al., 2010a; Fele et al., 2014; Hashemy Shahdany et al., 2017; Tian et al., 2019; Liu et al., 2023) and SIC2 (e.g., Alvarez et al., 2013; van Overloop et al., 2014; Horvath et al., 2015a,b; Segovia et al., 2019; Pour et al., 2022), are used as closed-loop simulation models. Using the same internal model for the closed-loop simulation is likely to lead to an overestimation of the MPC performance, but this is the solution adopted by many authors for two obvious reasons: (i) computation time reduction, and (ii) lack of more (refined) models readily available. For water reservoirs, only a few studies (e.g., Munier et al., 2015; Lin et al., 2020) have adopted a more refined and computationally-intensive model for the closed-loop simulation, which is essential to assess the robustness of the controller. Moreover, many studies, primarily on MPC applications in urban water networks, rely on simplified or synthetic systems (e.g., Sankar et al., 2015) due to the limited availability of calibrated high-fidelity models and the computational requirements of coupled hydraulic and water quality simulations of large-scale network systems models. While more computationally-efficient alternatives exist, including data-driven surrogate models (see Section 3.3), they often come with a tradeoff between computational savings and model accuracy. This should also be better quantified, possibly in relation to system size and characteristics.

Regarding the type of forecasts used in MPC (C3), various forecast variables, types and models emerge from the current literature, with differences depending on the type of water systems considered. In terms of forecasted variables, for water reservoirs, all the studies used either rainfall, inflow or tide forecasts. For urban water networks, water demand forecasts are mostly used, with a minority of studies also using rainfall/inflow or water levels. On the other hand, a more diverse set of forecasts are used for open channels, with more than half using water demand forecasts, less than half rainfall/inflow and a few other variables (see Table 1). In terms of the type of forecasts, for urban water networks, almost all the few studies relying on real (non-perfect) forecasts used statistical or ML-based models (e.g., Salvador et al., 2020; Dong and Yang, 2019). For open channels, six studies used statistical or ML-based models (e.g., Maestre et al., 2013; Tian et al., 2017b), five used process-based models (e.g., Xu et al., 2013; Aydin et al., 2019), and a single study used a hybrid approach (van Overloop et al., 2008). The picture is more complex for water reservoirs, for which the studies adopting real forecasts used more sources and forecasting techniques: less than half of them used well-established process-based hydrological models fed by operational meteorological forecasts (e.g., Wang et al., 2014; Raso et al., 2014; Ficchi et al., 2016) to produce the forecasts used in MPC, while slightly more than half used statistical or machine learning-based models that are calibrated on past observed data (e.g., Pianosi and Soncini-Sessa, 2009; Giuliani and Castelletti, 2013; Galelli et al., 2015; Gavahi et al., 2019). Only a few studies compared or integrated these two different techniques (Wei and Xun, 2019; Ahmad and Hussain, 2019). Given the recent increase in the availability of both real hydro-meteorological forecasts and efficient machine learning models, it is logical to expect benefits from more testing of hybrid forecast products in MPC and further applications are needed. Along the same lines, also the availability of forecasts at multiple timescales has been increasing, from short-range (few days) to seasonal- or long-range (up to 6-7 months or a year), and there is growing interest in seamless forecasts (e.g., Wetterhall and Di Giuseppe, 2018). However, there is a lack of research integrating multiple forecast products across time scales in MPC. Moreover, there is a lack of research investigating the dependence of the optimal prediction horizon and relative MPC performance on the accuracy of forecasts. The optimal horizon and the MPC performance are expected to be intensely dependent on the quality of the forecasts (e.g., Payet-Burin et al., 2021; Wei and Xun, 2019), and this dependence is not trivial due to the receding horizon and on-line update of the control strategy.

Finally, a key point for multipurpose water systems is that only a limited number of studies explored possible Multi-Objective (MO) MPC frameworks (e.g., Lin et al., 2020) typically required to address the tradeoffs across sectors by providing a set of Pareto-optimal solutions (C4). The majority of the reviewed papers rather compute a weighted sum of the objectives (e.g., Dong and Yang, 2019; Tedesco et al., 2016), which aggregates multiple objectives in an individual objective function, and some authors reduce the number of objectives by enforcing more constraints in the control problem. Further work is needed to explore Pareto-optimal solutions from MPC both at each control time step and over a long simulation horizon rolled by multiple receding horizons to account for the multi-objective nature of water systems' operation problems and enable tradeoff analysis.

Lastly, we noticed that the level of detail in reporting model description, optimal control problem formulation and explanation of the proposed control/management methodology is heterogeneous across the collection of reviewed papers. In many cases, there is no sufficient level of detail in the reviewed journal articles to allow for a full and fair comparison. A final recommendation is thus to develop a standardised framework to report key information on the essential components of future MPC studies (e.g., type of forecasts, system size and state variables, implemented optimisation method, benchmark methods, objective function, control variables, their number and their frequency) to facilitate comparison across studies, ultimately supporting knowledge transfer and reproducibility.

## 5. Conclusions

In recent years, Model Predictive Control has gained interest in the adaptive management of interconnected water resources systems, motivated by its capability of incorporating forecasts of evolving disturbances into a real-time optimal control scheme. Our comprehensive review of 149 peer-reviewed journal articles published in the last 20 years, selected after screening an originally more extensive set of 826 papers and checking them for eligibility, confirms an overall increasing adoption of MPC in all considered inter-connected sub-domains at the basin to urban scale, i.e., water reservoirs, open channels, and urban water networks. Despite the differences across these three types of systems, some common advantages, drawbacks, trends and challenges were identified in relation to MPC applications. In particular, our review identifies four main categories of challenges currently limiting most MPC applications in the water domain: (i) lack of systematic benchmarking of MPC with respect to other control methods and lack of assessment of the MPC performance in relation to the characteristics of the physical system; (ii) lack of assessment of the impact of uncertainties on the model-based control; (iii) limited analysis of the impact of diverse forecast types, resolutions, and prediction horizons; (iv) under-consideration of the multi-objective nature of most water resources systems. We argue that future MPC applications in water resources systems should focus on addressing these four challenges, as key priorities for future developments.

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**List of acronyms**

| | |
|---|---|
| ADP | Approximate Dynamic Programming |
| ANN | Artificial Neural Network |
| CSO | Combined Sewer Overflow |
| DDP | Deterministic Dynamic Programming |
| DSS | Decision Support System |
| EPANET | Environmental Protection Agency Network Evaluation Tool |
| ESP | Ensemble Streamflow Prediction |
| FQI | Fitted Q-Iteration |
| IPCC | Intergovernmental Panel on Climate Change |
| I | Integrator |
| ID | Integrator Delay |
| IDZ | Integrator Delay Zero |
| IR | Integrator Resonance |
| ISO | Implicit Stochastic Optimization |
| ML | Machine Learning |
| MO | Multi-Objective |
| MPC | Model Predictive Control |
| OC | Open Channel |
| OLFC | Open-Loop Feedback Control |
| PID | Proportional-Integral-Derivative |
| POLFC | Partial Open-Loop Feedback Control |
| PRISMA | Preferred Reporting Items for Systematic Reviews and Meta-Analyses |
| SDP | Stochastic Dynamic Programming |
| SWMM | Storm Water Management Model |
| SIC^2 | Simulation and Integration of Control for Canals |
| SOP | Standard Operating Procedure |
| SSDP | Sampling Stochastic Dynamic Programming |
| TB-MPC | Tree-Based Model Predictive Control |
| UWN | Urban Water Networks |
| WR | Water Reservoirs |

 

Table S1. Summary and classification of the 40 reviewed papers on MPC for water reservoirs (* denotes missing/unclear information).

| **Article** | **Forecast variable (disturbance)** | **Determinis-tic(D)/ Stochastic (S)/both (D&S)** | **Forecast type** | **Prediction horizon (max)** | **Ensemble size (1 for deterministic, n/a for explicit stochastic with pdf)** | **Operator over ensemble** | **Control frequency** | **Number of control actions** | **Type of control actions** | **MPC architecture (centralized/dece-ntralized/single-level/multi-level** | **Number of state variables** | **Number of objectives** | **Objective type** | **Benchmark method** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Castelletti et al. (2008) | inflow | D | perfect predictor, persistent predictor and statistical predictor | 1, 2, 4 days | 1 | n/a (D) | daily | 1 | release from reservoir | centralized, single level | 1 | 1 | flood control, water supply | SDP, historical operation |
| Pianosi and Soncini-Sessa (2009) | inflow PDF | S | (i) perfect predictor; (ii) statistical predictor (stochastic, Gaussian) | 1 day (up to 8 with perfect forecasts) | n/a | n/a | daily | 1 | release from reservoir | centralized, single level | 1 | 1 | flood control, water supply | off-line policy based on a more accurate model of the inflow |
| Blanco et al. (2010) | inflow (8 inflows) | D | a conceptual hydrological model fed by rainfall predictions | 30 hours | 1 | n/a (D) | hourly | 12 | water release (gate movement) | Centralized, single level | 75 | 1 | flood control | historical operation (a three-position controller based on a setpoint water level) |
| Romanowicz et al. (2010) | inflow | D | statistical predictions (nearest neighbour technique) | 30 days | 1 | n/a (D) | hourly | 1 | water release | centralized, single level | 1 | 1 | hydropower generation, environmental protection | n/a |
| Wang (2010) | inflow | S | statistical predictor, AR(1) model with error described as a white noise process | from 1 week to 1 year | 1 | n/a | weekly | 7 | release from reservoir | centralized, single level | 7 | 1 | hydropower production | SDP |
| Zambelli et al. (2011) | infow | D | statistical forecast using the monthly | 13 months to 24 months | 1 | n/a (D) | monthly | > 4 * | water release | centralized, single level | 5 | 1 | hydropower generation | SDDP |

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| | | | average of historical inflow records | (depending on current monthly stage) | | | | | | | | | | |
| Giuliani and Castelletti (2013) | inflow | D | a linear periodic PAR(1) model (at monthly time step) | 3 months | 1 | n/a (D) | monthly | 5 | release from reservoirs | (i) decentralized noncooperative setting; (ii) coordinated setting, with full information exchange; (iii) ideal centralized case, fully cooperative management. | 4 | 2 | hydropower production, environmental flow | n/a |
| Anand et al. (2013) | inflow | D | perfect predictor and statistical prediction with a randomly generated noise | 3 days | 1 | n/a (D) | daily | 2 | release from reservoirs | both centralized and decentralized configurations, with different levels of cooperation | 2 | 1 | hydropower generation, flood control, water supply | n/a |
| Breckpot et al. (2013) | inflow | D | * | * | 1 | n/a (D) | hourly | 1 | discharge at the 3 gates | Centralized, single level | * | 1 | flood control | n/a |
| Delgoda et al. (2013) | inflow | S | inflows predicted by a rainfall-runoff model (URBS) | 48 hours | 7 | expected value | hourly | 1 | release from reservoir | centralized, single level | 1 | 1 | flood control, water supply | historical operation |
| Galelli et al. (2014) | inflow and tide | D | two types: (i) ML-based (M5 tree), for inflows; (ii) a dynamic physically-based model, for tide predictions | 3 hours | 1 | n/a (D) | hourly | 3 | releases from reservoir gates, pumps, and drinking water intake pumps | centralized, single level | 1 | 1 | drinking water supply, flood control, pumps usage energy cost | SDP |
| Raso et al. (2014) | inflow | S | perfect forecasts and real forecasts from a conceptual hydrological model (HBV) | 15 days | 20 | tree | 6 hours | 2 | release from reservoir (controlled releases from the turbines and the spillways) | centralized, single level | 1 | 1 | hydropower production, flood control | n/a |
| Wang et al. (2014) | inflow | D | process-based (distributed physically-based hydrological model) fed by | 4 days | 1 | n/a (D) | daily | 3 | release from reservoir | centralized, single level | 3 | 1 | hydropower production, flood control | historical operation |

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| | | | operational precipitation forecasts | | | | | | | | | | | |
| Galelli et al. (2015) | inflow and tide | D | ML-based (M5 tree) and process-based dynamic predictions (inflows and tides), Dynamic Emulation Modeling procedure, for seawater intrusion | 3 hours | 1 | n/a (D) | hourly | 4 | release from reservoir, comprising the release from gates, pumps, bottom pipes, and drinking water intake | centralized, single level | 1 | 1 | drinking water supply, flood control, pumps usage energy cost, salinity level minimization | n/a |
| Kistenmacher and Georgakakos (2015) | inflow | S | statistically-based predictions (Historical Analog ESP) approach | 6 months | 15 | expected value | monthly | 7 | releases from six reservoirs and delta pumping | centralized, single level | 7 | 1 | environmental flow, storage target tracking, spillage excess cost reduction (energy generation maximisation), downstream water demand | n/a |
| Munier et al. (2015) | inflow | D&S | perfect predictions and real ones by a coupled model, hydrological (VIC) and hydrodynamic simplified routing (LLR) | > 30 days | 20 | n/a (D) * | daily | 1 | water release | Centralized, single level | * | 1 | low-flow augmentation (including environmental minimum flow) | n/a |
| Xu et al. (2015) | inflow | D | perfect predictions, statistical predictions (ARIMA model) | 13 years | 1 | n/a (D) | annual | 1 | release from reservoir | centralized, single level | 1 | 1 | water supply for urban demand, industry, environmental uses | historical operation; Standard Operating Procedure |
| Anghileri et al. (2016) | inflow | S | Perfect, climatology, probabilistic (ESP), hybrid (perfect forecast with climatology) | 365 days | 49 | expected value | daily | 1 | release from reservoir | centralized, single level | 1 | 1 | flood control, water supply (for urban, agricultural and environmental water demands) | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Fan et al. (2016) | inflow | D&S | perfect and real predictions by a hydrological model | 15 days, real predictions, and 60 days perfect forecasts | 16, reduced (51, original) | tree | daily | 1 | water release | Centralized, single level | 1 | 1 | hydroelectricity generation, flood control | n/a |
| Ficchì et al. (2016) | inflow | D&S | perfect and real predictions by a semi-distributed conceptual hydrological model fed by weather forecasts | 9 days | 6 (orig. 50) | tree | daily | 4 | releases from reservoirs | centralized, single level | 4 | 1 | flood control, water supply | historical operation (based on rule curves) |
| Karimanzira et al. (2016) | inflow | D | * | 21 days | 1 | n/a (D) | hourly | 10 | releases from reservoirs (total aggregated outflow, further split into turbine and spill flow) | centralized, single level | 10 | 1 | hydropower production, operational cost minimization, environmental requirements | n/a |
| Raso and Malaterre (2016) | inflow (forecast combined with climatology) | D | perfect, and statistical forecasts, combining real-time forecast and climatic information | infinite | 1 | n/a (D) | daily | 2 | releases from reservoir (release through turbines and the release trough spillages) | centralized, single level | 1 | 1 | flood and drought control, energy production | n/a |
| Wan et al. (2016) | inflow | S | statistical predictions (error fits a Gaussian distribution) | up to 50 days (forecasts horizon becomes shorter as it gets closer to the end of the simulatino period) | na | expected value | 5 days | 1 | water release | Centralized, single level | 1 | 1 | water supply, flood control | n/a |
| Zmijewski et al. (2016) | inflow | D | statistical predictions (based on historical data) | 120 hours (5 days) | 1 | n/a (D) | hourly | * (>50) | water release | Centralized, single level | * | 1 | hydropower generation | n/a |

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| Cuvelier et al. (2018) | inflow | S | * | 1 year | 1) na; 2) 22 | 1) For Stochastic optimization, the max function value is used; 2) For robust optimisation confidence intervals between 95% and 98.5% were tested | Up to a month | 1 | water release | Centralized, single level | 4 | 1 | water supply, flood control, environmental flow delivery, hydropower generation | historical operation |
| Myo Lin et al. (2018) | inflow | D | real forecasts produced by a semi-distributed conceptual rainfall-runoff model | 2 days | 1 | n/a (D) | 3 hours | 11 | releases from reservoirs | centralized, single level | 11 | 1 | flood control, water conservation | historical operation |
| Sahu and McLaughlin (2018) | inflow | S | synthetically generated ensemble following given distribution | * | na | expected value | na (1 time step) | 1 | water release | Centralized, single level | 1 | 1 | hydropower generation | DDP, SDP, historical operation |
| Uysal et al. (2018a) | inflow | D | perfect forecast, and synthetic deterministic forecast, produced perturbing observations with random noise | 3 days | 1 | n/a (D) | daily | 1 | release from reservoir (spillway release) | centralized, single level | 1 | 1 | flood control, water supply, operation costs (e.g., excessive spillages) | feedback control with Rule Curves (RC, or Guide Curves) |
| Uysal et al. (2018b) | inflow | D&S | Perfect Forecasts and Probabilistic Streamflow Forecasts synthetically generated | 48 hours | 50 | tree | hourly | 1 | release from reservoir (spillway release) | centralized, single level | 1 | 1 | flood control (setpoint for forebay elevation), water supply, operational cost | n/a |
| Ahmad and Hossain (2019) | inflow | S | ANN fed with real weather forecasts (GEFS) and antecedent hydrological variables | 7 days | 11 | min, max, average | daily | 1 | release from reservoir | centralized, single level | 1 | 1 | hydropower production, flood control and dam safety | historical operation, SDP |

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| Arsenault and Cote (2019) | inflow | S | statistical based on historical climate data. (a year is considered one ensemble member) | 120 days (4 months) | 25 | Median and quantiles (or member by member) | 3 days | 5 | release from reservoirs (water withdrawn) | Centralized, single level | 5 | 1 | hydropower generation | n/a |
| Gavahi et al. (2019) | inflow | D | perfect forecasts and data-driven forecasts produced by an adaptive neuro-fuzzy inference system | 12 months | 1 | n/a (D) | monthly | 3 | release from reservoir and water allocations to each water use sector | centralized, single level | 1 | 1 | water supply, environmental flow | historical operation and rule curves obtained by a long-term optimization model |
| Roetz and Theobald (2019) | inflow | D | real deterministic forecasts from conceptual rainfall-runoff model (HBV) | 160 hours (6.7 days) | 1 | n/a (D) | 10 hours | 1 | release from reservoir | centralized, single level | 1 | 1 | flood control, navigation (reference set point) | n/a |
| Wei and Xun (2019) | inflow | D | hybrid, combination of conceptual rainfall–runoff model and multiple linear regression model | 10 days | 1 | n/a (D) | daily | 1 | water release | Centralized, single level | 1 | 1 | hydropower generation | n/a |
| Myo Lin et al. (2020) | inflow | D | real deterministic forecasts from conceptual rainfall-runoff model (Sacramento) | 2 days | 1 | n/a (D) | 30 min | 11 | release from reservoir | centralized, single level | 11 | 3 | flood control, hydropower generation, reservoir storage reference target (deviation) | n/a |
| Xu et al. (2020) | inflow | S | Statistical (errors modelled by a copula function) | 24 hours | na | expected value | hourly | 1 | water release | Centralized, single level | 4 | 3 | domestic water supply, irrigation, flood control | * |
| Payet-Burin et al. (2021) | inflow | S | nearest neighbor bootstrapping to generate an ensemble forecast | 2 years | 2 (original 20) | expected value | monthly | 4 | release from reservoir | centralized, single level | 4 | 1 | economic benefits (water demand satisfaction), hydropower production; water supply, environmental | SDP, DDP |

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| | | | | | | | | | | | | | flow, hydropower | |
| Salehi and Shourian (2021) | inflow | D | * | 15 days | 1 | n/a (D) | daily | 14 | 10 reservoir releases and 4 pumping stations commands | centralized, single level | 14 | 2 | operational costs of safe reservoir storage target, reduction of fluctuations in pump stations | Metaheuristic search with Particle Swarm Optimization (PSO) |
| Kergus et al. (2022) | inflow | D | perfect precictions and stastical predictions modelled with a random noise added on the disturbances | 15 days (chosen after testing 10, 15 and 20 days) | 1 | n/a (D) | daily | 1 | water release | Centralized, single level | 1 | 1 | hydropower production, flood control | SDP, DDP |
| Mohanavelu et al. (2022) | inflow | D | perfect forecast (Random Noise level assumed as perfect prediction) | * | 1 | n/a (D) | daily | 1 | release from reservoir | centralized, single level | 1 | 2 | flood control, irrigation supply | DDP, SDP, ISO, FQI, SSDP |

Table S2. Summary and classification of the 58 reviewed papers on MPC for open channels.

| Article | Forecasted variable (disturbance) | Deterministic(D)/ Stochastic (S)/both (D&S) | Forecast type | Prediction horizon length (max) | Ensemble size (1 for deterministic, n/a for explicit stochastic with pdf) | Control frequency | Number of control actions | Type of control actions | MPC architecture (Centralized/decentralized/single-level/multi-level) | Num. of state variables | Prediction model | Num of objectives | Objective type | Benchmark method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | | |
| Wahlin (2004) | flow rate changes at turnouts | D | perfect knowledge | 200 minutes | 1 | 5 minutes | 8 | changes in flow rate at the check structures | centralized, single-level | 29 | ID | 2 | water level setpoint tracking, control smoothness | PI |
| Wahlin and Clemmens (2006a) | demands | D | (i) perfect knowledge (ii) no knowledge | 20 hours | 1 | 30 minutes | 31 | gate flow | centralized, single-level | 31 | ID | 2 | water level setpoint tracking, control smoothness | LQR |
| Wahlin and Clemmens (2006b) | offtake flows | D | n/a | n/a | 1 | 1 minute | 4 | n/a | centralized, single-level | 12 | ID | 2 | water level setpoint tracking, control smoothness | PI |
| van Overloop et al. (2008) | precipitation | S | hybrid | 1 day | 3 | 15 minutes | 1 | pump flow | centralized, single-level | 4 | ID | 4 | water level setpoint tracking, control smoothness, water level rate of change setpoint tracking, bounded water levels | PI |
| Lemos et al. (2009) | offtake flows | D | perfect knowledge | 75 seconds | 1 | 5 seconds | 4 | gate and valve position | centralized, single-level | 12 | spatial discretization | 3 | water level setpoint tracking, control smoothness, control effort | PI(D) |
| Negenborn et al. (2009) | rainfall offtakes by farmers | D | perfect knowledge | 124 minutes | 1 | 4 minutes | 7 | gate inflow | distributed, single-level | 30 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| van Overloop et al. (2010a) | delivery changes | D | perfect knowledge | 2 hours | 1 | 4 minutes | 8 | gate flow | centralized, single-level | 8 | ID | 3 | water level setpoint tracking, control | LQR |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | smoothness error rate of change tracking | |
| Xu et al. (2011) | rain and lateral inflows | D | perfect knowledge | 2 hours | 1 | 4 minutes | 1 | gate flow | centralized, single-level | 10 | spatial discretization | 2 | water level setpoint tracking, control smoothness | n/a |
| Zafra-Cabeza et al. (2011) | rainfall, irrigation demands | D | (i) perfect knowledge (ii) no knowledge | higher level: 5 days, lower level: 5 minutes | 1 | higher level: 1 day, lower level: 1 min | higher level: 6, lower level: 7 | higher level: mitigating actions, lower level: gate position | distributed, multi-level | higher level: 8, lower level: 7 | ID | (i) 2; (ii) 2 | higher level: minimize risks and control effort, · lower level: water level and control setpoint tracking | n/a |
| Wagenpfeil et al. (2012) | lock operations, wind and inflows | D | statistical and lack of knowledge (estimate) | 48 hours | 1 | 15 minutes | n/a | pump flow | centralized, single-level | 46 | spatial discretization | 2 | water level setpoint tracking, control smoothness | n/a |
| Xu et al. (2012) | upstream inflow | D | perfect knowledge | 2 hours | 1 | 4 minutes | 1 | gate discharge | centralized, single-level | 500 | spatial discretization | 2 | water level setpoint tracking, control smoothness | n/a |
| Alvarez et al. (2013) | offtake flows | D | perfect knowledge | n/a | 1 | 6 minutes | 5 | gate flow and opening | distributed, single-level | 5 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Breckpot et al. (2013) | offtake flows | D | perfect knowledge | 225 minutes | 1 | 15 minutes | 4 | gate discharge | centralized, single-level | 7 | spatial discretization | 4 | water level setpoint tracking, control smoothness, flooding, safety limits | n/a |
| Doan et al. (2013) | n/a | D | n/a | 5 hours | 1 | 30 minutes | 12 | dam, turbine, and pump flow | distributed, single-level | 32 | spatial discretization | 3 | power production profile tracking, water level setpoint tracking, control smoothness | n/a |
| Figueiredo et al. (2013) | offtake flows | D | n/a | 6 minutes | 1 | 10 seconds | 5 | gate flow, valve position | centralized, single-level | 85 | spatial discretization | 3 | water level setpoint tracking, control smoothness, operational costs | PI |

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| Hashemy et al. (2013) | offtake flows | D | perfect knowledge | 7 hours | 1 | 5 minutes | 13 | gate discharge | centralized, single-level | 64 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Maestre et al. (2013) | runoff (as a result of rainfall) | D&S | statistical | 4 hours | 6 | 15 minutes | 1 | pump flow | distributed, single-level | 3 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Romera et al. (2013) | upstream inflow | D | perfect knowledge | 70 minutes | 1 | 100 seconds | 3 | gate openings | centralized, single-level | 3 | IDZ | 3 | flooding, safe water evacaution, control smoothness | n/a |
| van Ekeren et al. (2013) | river inflows and sea levels | D | perfect knowledge | 1 day | 1 | 30 minutes | 3 | barrier and sluice position | centralized, single-level | 4 | I | 3 | flooding, economic costs, control smoothness | n/a |
| Xu et al. (2013) | lateral discharges and pollution concentrations | D | process-based | 2 hours | 1 | 4 minutes | 5 | gate and pump flow | centralized, single-level | 20 | spatial discretization | 4 | water level setpoint tracking, control smoothness, bounded water quality, bounded water levels | n/a |
| Fele et al. (2014) | offtake flows | D | perfect knowledge | 50 minutes | 1 | 5 minutes | 13 | gate discharge | distributed, multi-level | 39 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Foo et al. (2014) | irrigation demands, creek inflows, surface-groundwater interaction | D | perfect knowledge | 4 days | 1 | 6 hours | 3 | gate, creek and lake flow | centralized, single-level | 32 | ID | 9 | water demand satisfaction, off-stream storage volume. environmental minimum flow, bounded water levels, flow setpoint tracking limit lake releases, water ordering time, bounded seasonal flows, control smoothness | PI |
| Sadowska et at. (2014) | offtake flows | D | n/a | 9 hours | 1 | 15 min | 10 | gate position | decentralized, multi-level | 10 | spatial discretization | 4 | flow setpoint tracking, bounded control | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | actions, water level setpoint tracking, water level setpoint reset | |
| van Overloop et al. (2014) | downstream gate discharge | D | (i) perfect knowledge (ii) no knowledge | 200 seconds | 1 | 10 seconds | 1 | gate discharge | centralized, single-level | 1 | IR | 2 | water level setpoint tracking, control smoothness | n/a |
| Horvath et al. (2015a) | offtake flows | D | (i) perfect knowledge (ii) no knowledge | 150 seconds | 1 | 10 seconds | 3 | gate position | centralized, single-level | 3 | IR | 2 | water level setpoint tracking, control smoothness | n/a |
| Horvath et al. (2015b) | discharge and setpoint changes | D | (i) perfect knowledge (ii) no knowledge | n/a | 1 | 10 seconds | 3 | gate position and discharge | centralized, single-level | 3 | IR | 2 | water level setpoint tracking, control smoothness | n/a |
| Sadowska et at. (2015) | delivery requests | D | perfect knowledge | 320 minutes, 480 minutes | 1 | 20 min | 8 | gate discharge | decentralized, multi-level | 7 | ID | 4 | flow setpoint tracking, bounded control actions, water level setpoint tracking, water level setpoint reset | n/a |
| Shahdany et al. (2015) | offtake flows | D | perfect knowledge | 7 hours | 1 | 5 min | 26 | gate discharge | centralized, single-level | 76 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Tian et al. (2015) | river discharges and tidal levels | D | n/a | 2-6-10 days | 1 | 1-2-3-4-6 hours | 11 | gate position | centralized, single-level | 40 | spatial discretization | 2 | water level setpoint tracking, control smoothness | n/a |
| van Overloop et al. (2015) | water orders | D | perfect knowledge | 4 hours | 1 | 5 min | 14 | gate discharge | centralized, single-level | 13 | ID | 2 | water level setpoint tracking, control smoothness | PI |
| Farhadi and Khodabandehlou (2016) | offtake flows | D | perfect knowledge | 90 min | 1 | 9 min | 4 | gate position | distributed, multi-level | 22 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Shahdany et al. (2016) | offtake flows | D | perfect knowledge | 2 hours | 1 | 5 min | 10 | gate discharge | centralized, single-level | 20 | ID | 2 | water level setpoint tracking, | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | control smoothness | |
| Aydin et al. (2017) | outflow discharge | D | lack of knowledge (estimate) | 200 seconds | 1 | 10 seconds | 1 | n/a | centralized, single-level | 1 | IR | 2 | water level setpoint tracking, control smoothness | n/a |
| Hashemy Shahdany et al. (2017) | offtake demands | D | n/a | 3 hours | 1 | 5 minutes | n/a | gate discharge | centralized, single-level | n/a | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Tian et al. (2017a) | upstream inflow | D | perfect knowledge | 1 day | 1 | 1 hour | 1 | pump flow | centralized, single-level | 1 | I | 2 | water level setpoint tracking, control smoothness | n/a |
| Tian et al. (2017b) | inflows | D&S | statistical | 24-72-144 hours | 20 | 1-2-4 / 1-3-6 h | 2 | pump flow, gate height | centralized, single-level | 3 | spatial discretization | 2 | water level setpoint tracking, control smoothness | n/a |
| Xu (2017) | irrigation offtake flows | D | perfect knowledge | n/a | 1 | n/a | 8 | gate discharge | centralized, single-level | 7 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Xu and Schwanenberg (2017) | n/a | D | n/a | n/a | 1 | 1 hour | 3 | gate position | centralized, single-level | 15 | spatial discretization | 2 | water level setpoint tracking, control smoothness | n/a |
| Aydin et al. (2019) | groundwater exfiltration concentration, discharge | D | process-based | 1 hour | 1 | 2 min | 4 | n/a | centralized, single-level | 24 | spatial discretization | 3 | water level setpoint tracking, salinity setpoint tracking, freshwater use | n/a |
| Kong et al. (2019a) | offtake flows | D | (i) perfect knowledge (ii) no knowledge | 5 hours | 1 | 10 min | 5 | gate discharge | centralized, single-level | 34 | ID | 2 | water level setpoint tracking, control effort | LQR |
| Kong et al. (2019b) | offtake flows | D | (i) perfect knowledge (ii) no knowledge | 700min | 1 | 10min | 26 | n/a | centralized, single-level | 98 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Segovia et al. (2019) | lock operations | D | perfect knowledge | 4 hours | 1 | 20 min | 4 | gate and weir flow | centralized, single-level | 6 | IDZ | 4 | water level setpoint tracking, operational costs, control | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | | smoothness, navigability | |
| Shahdany et al. (2019) | offtake flows | D | (i) perfect knowledge (ii) no knowledge | 6 hours | 1 | 5 min | 16 | n/a | centralized, single-level | 96 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Tian et al. (2019) | inflows | S | statistical | 6 hours | 20 | 1 hour | 1 | n/a | centralized, single-level | 1 | n/a | 2 | bounded water levels, water level setpoint tracking | n/a |
| Velarde et al. (2019) | inflows | S | statistical | 1 day | 20 | 1 hour | 3 | gate position, pump flow | distributed, multi-level | 2 | I | 2 | water level setpoint tracking, control smoothness | n/a |
| Zheng et al. (2019) | offtake flows | D | (i) perfect knowledge (ii) no knowledge | 40 min | 1 | 2 min | 4 | n/a | centralized, single-level | 4 | ID | 2 | water level setpoint tracking, control effort | PI, LQR |
| Rodriguez et al. (2020) | n/a | D | lack of knowledge (estimate) | 215 min | 1 | 5 min | 24 | n/a | centralized, single-level | 144 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Zhu et al. (2020) | n/a | D | perfect knowledge | 10 min | 1 | 10 min | 2 | gate position | centralized, single-level | 3 | ID | 3 | reduce pressure at a cross section, bounded water levels, overtopping | n/a |
| Kong et al. (2021) | (i) unknown offtakes, (ii) scheduled offtakes | D | (i) perfect knowledge (ii) no knowledge | 24 hours | 1 | 30 min | 13 | n/a | centralized, single-level | 65 | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Nasir et al. (2021) | offtake flows | S | statistical | 40 min | 646 | 10 min (simulation), 9 min (field test) | 8 (simulation), 3 (field test) | n/a | decentralized, multi-level | 8 (simulation), 3 (field test) | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Ren et al. (2021) | offtake demands | D | n/a | n/a | 1 | n/a | n/a | gate opening | centralized, single-level | n/a | model-free | 3 | water level setpoint tracking, control smoothness, early gate adjustments | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Askari Fard et al. (2022) | offtake demands | D | process-based | n/a | 1 | n/a | 17 | n/a | centralized, single-level | n/a | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Avargani et al. (2022) | offtake demads | D | process-based | n/a | 1 | n/a | 14 | n/a | centralized, single-level | n/a | ID | 2 | water level setpoint tracking, control smoothness | n/a |
| Aydin et al. (2022) | lateral flows and concentrations | D | process-based | 24 hours | 1 | 1 hour | 42 | n/a | centralized, single-level | 522 | spatial discretization | 2 | salinity setpoint tracking, water level setpoint tracking, | n/a |
| Horvath et al. (2022) | in- and outflows of canals | D | perfect knowledge | 12 hours | 1 | 1 hour | 28 | gate, pump and weir discharge | centralized, single-level | 25 | I | 4 | water storage and transportation, agricultural demands water levels for safety, navigation and preserve ecology, economic costs | n/a |
| Pour et al. (2022) | tidal pattern | D | perfect knowledge | 12 hours | 1 | 20 min | 8 | gate and pump flow | centralized, multi-level | 4 | IDZ | 5 | water level setpoint tracking, energy production, operational costs, control smoothness, navigability | n/a |
| van der Heijden et al. (2022) | hydrological forcings, electricity market data | D | perfect knowledge | 48 hours | 1 | 15 min | 2 | gate and pump flow | centralized, single-level | 1 | I | 3 | day-ahead bidding costs, intraday trading costs, energy use in pumping | n/a |
| Liu et al. (2023) | offtake flows | D | n/a | n/a | 1 | 5 minutes | 36 | gate flow rate | centralized, single-level | n/a | ID | 2 | water level setpoint tracking, control smoothness | PI(D), LQR |

 

Table S3. Summary and classification of the 49 reviewed papers on MPC for urban water networks.

| Article | Forecasted variable (disturbance) | Deterministic(D)/ Stochastic (S)/both (D&S) | Forecast type | Prediction horizon length (max) | Ensemble size (1 for deterministic, n/a for explicit stochastic with pdf) | Control frequency | Number of control actions | Type of control actions | MPC architecture (Centralized/decentralized/single-level/multi-level) | Num. of state variables | Network type and size | Num of objectives | Objective type | Benchmark method |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Marinaki et al., 1999 | Inflow | D | Perfect predictions | 4 hours | 1 | 1 min | 10 | Reservoir outflow | Centralized | 208 | Sewer network (simplified) | 1 | Minimize relative storage differences, control smoothness | Nonlinear optimal control |
| Biscos et al. (2002) | Water demand | D | n/a | 12 hours | 1 | n/a | n/a | n/a | n/a | n/a | Distribution network (Simplified: 5 reservoirs, 2 pump stations, 3 splits) | 1 | n/a | n/a |
| Biscos et al. (2003) | Water demand | D | n/a | 8 hours | 1 | 1 hour | 5 | Valves and pumps | Centralized | n/a | Distribution networks (Small, artificial: 5 reservoirs, 4 valves, 1 pump) | 1 | Economic cost, chlorine concentration | n/a |
| Rao and Salomons (2007) | n/a | D | n/a | 24 hours | 1 | 1 hour | 3 | Valves and pumps | Centralized | n/a | Water distribution network (simplified) | 1 | n/a | n/a |
| Darsono et al. (2007) | n/a | D | n/a | | 1 | n/a | 28 | Pumps | Centralized | n/a | Combined sewer system (26000 ha) | 1 | n/a | n/a |
| Martinez et al. (2007) | n/a | n/a | n/a | 24 hours | 1 | 1 hour | 27 | Valves and pumps | Centralized | 2 | Water distribution network (725 nodes) | 1 | n/a | n/a |
| Salomons et al. (2007) | Water demand | D | n/a | 24 hours | 1 | 1 hour | 23 | Valves and pumps | Centralized | 9 | Water distribution network (Simplified: 126 pipes, 112 nodes, 9 storage tanks, 1 operating valve and 17 pumps in 5 discrete pumping stations) | n/a | n/a | n/a |
| Muslim et al. (2008) | | | n/a | | 1 | n/a | 3 | | n/a | n/a | Drinking water networks | n/a | Chlorine concentration | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shamir and Salomons (2008) | Water demand | D | Synthetic (based on historical data and another system) | 1 day | 1 | hourly | 25 | Valves and pumps | Centralized | 9 | Water distribution system (Simplified - Full model: 867 nodes, 987 pipes, 9 tanks, 17 pumps in 5 pumping stations, and 8 pressure reducing valves; Reduced model: 77 nodes, 92 pipes. 9 tanks, 17 pumps in 5 pumping stations, and 8 pressure reducing valves) | 1 | Pump energy cost | Rule-based control |
| Puig et al. (2009) | n/a | D | n/a | n/a | 1 | n/a | n/a | Gates | Centralized | n/a | Sewer networks (Real-world) | 1 | Minimize overflow, CSO discharges, maximize WWTP usage | Local controls |
| Cembrano et al. (2011) | Water demand | D | n/a | 24 hours | 1 | 1 hour | 127 | Valves and pumps | Centralized | n/a | Distribution networks (Real-world: 281 pressure mains, 99 tanks, 88 valves, 39 pumping stations) | 1 | Economic cost, tank storage safety, control smoothness, pressure control | n/a |
| Pascual et al. (2013) | Water demand | D | ARX-based | 24 hours | 1 | 1 hour | 129 | Valves and pumps | Centralized | n/a | Transport networks (Real-world: 63 tanks, 3 surface sources, 7 undergraound sources, 79 pumps, 50 valves, 18 nodes, 88 demands) | 1 | Economic cost, tank storage safety, control smoothness | Rule-based control |
| Bakker et al. (2013) | n/a | n/a | n/a | n/a | 1 | n/a | n/a | | n/a | n/a | Water supply systems | n/a | n/a | Rule-based control |
| Fiorelli et al. (2013) | n/a | D | n/a | 24 hours | 1 | 15 minutes | 5 | Flow | Centralized | 4 | Water distribution network (simplified) | 1 | n/a | n/a |
| Joseph-Duran | n/a | D | n/a | | 1 | n/a | n/a | Gates | Centralized | 12 | Combined sewer system (simplified) | 1 | n/a | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| et al. (2013) | | | | | | | | | | | | | | |
| Joseph-Duran et al. (2014) | Rainfall | D | n/a | 30 minutes | 1 | 5 minu tes | 10 | Gates | Centralized | n/a | Sewer networks (Simplified: 145 sewers, 68 rain inflows) | 1 | Minimize overflow, CSO discharges, maximize WWTP usage | n/a |
| Grosso et al. (2014) | Water demand | S | BATS, time-series model | 24 hours | | 1 hour | 114 | Valves and pumps | n/a | n/a | Drinking water networks (63 tanks, 114 actuators) | 1 | Economic cost, tank storage safety, control smoothness | n/a |
| Limon et al. (2014) | Water demand | D | n/a | 24 hours | 1 | 1 hour | 6 | Flow | Centralized | 3 | Drinking water transport network (Simplified: 3 tanks, 6 actuators) | 1 | n/a | n/a |
| Joseph-Duran et al. (2015) | Rainfall | D | n/a | 200 minutes | 1 | 5 minu tes | 10 | Gates | Centralized | n/a | Sewer networks (simplified: 145 sewers, 68 rain inflows) | 1 | Minimize overflow, CSO discharges, maximize WWTP usage | n/a |
| Sankar et al. (2015) | Water demand | D | n/a | 24 hours | 1 | 1 hour | 2 | Valves and pumps | Centralized | n/a | Distribution networks (Very small: 11 nodes, 2 valves, 1 reservoir, 2 demand nodes) | 1 | Track setpoint of outlofw rate from demand nodes | n/a |
| Grosso et al. (2016) | Water demand | S | n/a | 24 hours | n/a | 1 hour | 118 | Flow | Centralized | 63 | Drinking water transport network (simplified) | 1 | n/a | n/a |
| Pereira et al. (2016) | Water demand | D | n/a | 24 hours | 1 | 1 hour | 61 | Flow | Centralized | 17 | Drinking water transport network (simplified: 17 tanks, 12 node, 25 demands) | 1 | n/a | n/a |
| Sun et al. (2016) | n/a | D | n/a | n/a | 1 | n/a | 3 | Pumps | Centralized | 4 | Water distribution network (simplified: 1 reservoir, 4 tanks, 7 pumps) | 1 | n/a | n/a |
| Grosso et al. (2017) | Water demand | S | ARIMA | 24 hours | n/a | 1 hour | 61 | Valves and pumps | Centralized | n/a | Drinking water network (simplified: 17 tanks, 61 flows controlled by valves and pumps, 25 demand nodes, 9 water sources, | 1 | Economic cost | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | 11 intersection nodes) | | | |
| Wang et al. (2017) | Water demand | D | n/a | 24 hours, 1 hour (2 layer approach) | 1 | 1 hour / 1 minute (2 layer approach) | 16 | Valves and pumps | Hierarchical | n/a | Distribution network (artificial: 399 junctions, 7 tanks, 11 pumps, 5 valves) | 1 | Economic cost, tank storage safety, control smoothness | n/a |
| Wang et al. (2018) | Water demand | D | n/a | 24 hours | 1 | n/a | 7 | Pumps | n/a | n/a | Distribution networks (simplified: 6 tanks, 7 pumps, 11 water demand sectors, 41 non-storage nodes) | 1 | Economic cost, tank storage safety, control smoothness | n/a |
| Tedesco et al. (2018) | Water demand | D | Perfect predictions | 24 hours | 1 | 1 hour | 121 | Valves and pumps | Centralized | 67 | Water transport network (Real-world: 67 tanks and 121 actuators (46 pumps and 75 valves), 88 water demand sectors and 16 nodes) | 1 | n/a | Centralized vs distributed command governor appeoaches |
| Pour et al. (2019) | Water demand | D | n/a | 24 hours | 1 | 1 hour | 61 | Flow | Centralized | 17 | Drinking water transport network (simplified: 17 tanks, 12 node, 25 demands) | 1 | n/a | n/a |
| Housh and Salomons (2019) | | n/a | n/a | | n/a | n/a | n/a | Pumps | n/a | 1 | Water distribution network (1 node) | n/a | n/a | n/a |
| Wang et al. (2020) | Water demand | D | n/a | 6 hours | 1 | 1 hour | 10 | Valves and pumps | Centralized | n/a | Drinking water network (Real-world simplified: 126 nodes) | 1 | n/a | Rule-based control |
| Salomons and Housh (2020) | Water demand | D | n/a | 48 hours | 1 | 1 hour | 8 | Valves and pumps | Centralized | n/a | Distribution networks (Real-world: 5 wells, 3 variable speed pumps, 5 constant speed pumps, 8 tanks, 8 junctions) | 1 | Minimize cost | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Liu et al. (2020) | Water demand | D | n/a | 25 minutes | 1 | 5 minutes | 9 | Flows | n/a | n/a | Distribution networks (simplified: 2 water plants, 6 pump stations, 4 tanks, 4 water distribution areas) | 2 (switching according to a condition, 1 objective in each zone) | n/a | n/a |
| Sun et al. (2020) | Rainfall | D | n/a | 30 minutes | 1 | 5 minutes | 3 | Gates and pumps | Centralized | n/a | Sewer networks integrated with WWTPs in a sanitation system (Real-world: 1 tank, 2 gates, 1 pump) | 1 | CSO minimization, WWTP usage maximization , smoothness, pollution minimization | Rule-based control |
| Pour et al. (2020) | Water demand | S | n/a | 24 hours | | 1 hour | 61 | Flow | Centralized | 17 | Drinking water transport network (simplified: 17 tanks, 12 node, 25 demands) | 1 | n/a | n/a |
| Salomons & Housh (2020) | | D | n/a | n/a | 1 | n/a | n/a | Flow | | | Water distribution network | n/a | n/a | n/a |
| Salvador et al. (2020) | Water demand | S | Statistical (periodic signal) | n/a | n/a | hourly | 7 | Pumps | Centralized | 6 | Water distribution network (Real-world: 6 tanks, 7 pumps, 41 nodes (11 demand nodes), 44 pipes) | 1 | Keep tank level around a set-point | n/a |
| Dong and Yang (2020) | Water level; water quality indices | D | ML-based (LSTM) | 1 day | 1 | daily | 4 | Pumps | Centralized | n/a | Drainage system (Real-world) | 1 | Weighted objective: electricity cost for pumping and pump start-up cost | n/a |
| Wang et al. (2021) | n/a | D | n/a | 24 hours | 1 | 1 hour | 3 | Flow | Centralized | 1 | Water distribution network (Simplified: 1 tank, 3 pumps) | 1 | | Rule-based control |
| Wang et al. (2021) | n/a | D | n/a | n/a | 1 | n/a | n/a | Sluices regulation | n/a | n/a | Drainage area (Real-world: big area with 5 lakes) | n/a | n/a | Rule-based control |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| van der Werf et al. (2021) | n/a | D | n/a | n/a | 1 | n/a | 2 | Control stations | Centralized | 14 | Urban drainage system (simplified: 14 reservoirs, 2 control stations) | 1 | n/a | Rule-based control |
| Svensen et al. (2021) | n/a | | n/a | 100 minutes | | 5 minutes | | | | 6 | Urban drainage system (simplified) | n/a | n/a | |
| Shishegar et al. (2021) | Rainfall | D | Physically-based | 48 hours | 1 | 2 hours | 4 | Basin outflow | Centralized | 4 | Drainage network (Real-world, simplified: 526 nodes, 544 links) | 1 | Minimum total peak flow discharge from stormwater system, smoooth operations | Static control |
| Trapiello et al. (2021) | Water demand | D | Maximum expected demand from past data | | 1 | 1 hour | 26 | Actuator activation (pumps) | Centralized | 17 | Water transport network (simplified: 9 water sources (5 underground and 4 superficial), 17 water tanks, 61 actuators (37 valves and 24 pumps), 12 nodes and 25 demands) | 2 | Minimize the number of back-up actuators used, minimize the performance loss during a given time horizon | n.a. |
| El Ghazouli et al. (2022) | Wastewater and ranwater flows | D | ANNs | n/a | 1 | n/a | n/a | | n/a | n/a | Sewer networks | n/a | n/a | n/a |
| Martin et al. (2022) | Water demand | D | n/a | 5 seconds | 1 | 0.1 seconds (may be typo in paper?) | n/a | Valves | Decentralized | n/a | Drinking water networks (Real-world, simplified) | 1 | Smoothness, tracking valve reference | n/a |
| Pedrosa et al. (2022) | n/a | D&S | n/a | 24 hours | n/a | 1 hour | 61 | Flow | Centralized | 17 | Drinking water transport network (simplified: 17 tanks, 12 node, 25 demands) | 1 | n/a | n/a |
| Guo et al. (2022) | Water demand | D | n/a | 24 hours | 1 | 1 hour | 6 | Flow | Centralized | 3 | Water distribution network (simplified: 25 nodes, 3 tanks) | 1 | n/a | n/a |

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|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Kändler et al. (2022) | Head | n/a | n/a | 5 min | n/a | Unclear | 1 | Valves | Centralized | n/a | Urban drainage system (Real-world: tot pipe length 7.1 km) | n/a | n/a | Rule-based control |