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Author/s:
Nasir, HA;Zhao, T;Carè, A;Wang, QJ;Weyer, E

Title:
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Date:
2018-01-01

Citation:
Nasir, H. A., Zhao, T., Carè, A., Wang, Q. J. & Weyer, E. (2018). Efficient River Management using Stochastic MPC and Ensemble Forecast of Uncertain In-flows *. IFAC Papersonline, 51 (5), pp.37-42. https://doi.org/10.1016/j.ifacol.2018.06.196.

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IFAC PapersOnLine 51-5 (2018) 37–42

Efficient River Management using Stochastic MPC and Ensemble Forecast of Uncertain In-flows ⋆

Hasan Arshad Nasir* **Tony Zhao**** **Algo Carè***** **Quan J. Wang**** **Erik Weyer***

* *Department of Electrical and Electronic Engineering, The University of Melbourne, 3010, Victoria, Australia. (email: {hanasir,ewey}@unimelb.edu.au)*

** *Department of Infrastructure Engineering, The University of Melbourne, 3010, Victoria, Australia. (email: {tony.zhao,quan.wang}@unimelb.edu.au)*

*** *Department of Information Engineering, University of Brescia, via Branze, 38 25123 Brescia, Italy. (email: algo.care@unibs.it)*

Abstract: Efficient river management is essential in improving water resource utilisation. However, river flows and water-levels are affected by unregulated in- and out-flows. Therefore, it is important to consider the forecasts of these unregulated flows and the uncertainties in the forecasts. The paper describes control and modelling tools from the literature that suit the river management problem. Specifically, a scenario-based Stochastic Model Predictive Control (MPC) strategy, that makes use of ensemble forecast of unregulated flows, is proposed, where the ensemble forecast contains multiple flow scenarios to characterise future flows and their uncertainties, and are obtained from catchment hydrological models.

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Keywords: River Management; Stochastic Model Predictive Control; Chance-Constrained Optimisation Problem; Scenario Approach; Ensemble Forecast; Hydrological Modelling;

1. INTRODUCTION

Water is a precious resource. Large efforts have gone into achieving efficient water resource management in the last few decades, and many works have appeared on modelling and control of water systems. E.g. (Cantoni et al. (2007); Litrico et al. (2005); Nasir and Muhammad (2011); Weyer (2008); Van Overloop et al. (2005)) have demonstrated improvements in the water distribution efficiency for irrigation channels. Similarly, several works on control and management of rivers are also available, see e.g. (Foo et al. (2012); Litrico (2002); Nasir and Weyer (2016); Young et al. (2007); Nasir et al. (2018); Setz et al. (2008); Corani and Guariso (2005); Pianosi et al. (2012); Turner et al. (2017); Labadie (2004); Castelletti and Soncini-Sessa (2007)).

Rivers play a major role in the timely delivery of water for agricultural, urban and environmental needs. Rivers usually have long time delays because of the long reaches, i.e., locations where flows can be regulated are often far away from locations where the controlled variable is measured, e.g. at the off-take point to an irrigation channel or urban water supply. As a result, forecasts of unregulated in- and out-flows along a reach must be taken into account for efficient management. For the unregulated flow forecasting, hydrological models (Cloke and Pappenberger (2009); Bennett et al. (2016)) are usually required that provide a relationship between the precipitation and the streamflows. However, the flow forecasts are uncertain, and thus a hydrological model that can also quantify the uncertainties in the forecasts is vital in decision making. If the unregulated flow forecasts and the associated uncertainties are not considered in the management process, it can cause flooding or water scarcity. Similarly, evaluating the effects of, e.g., unregulated in-flows to the whole river, especially at the downstream end of a long river, and their variations throughout a season, are essential in river management. Furthermore, timely inundation of wetlands and floodplains to meet environmental requirements is also critical for healthy rivers. For more details on water and river management issues, see e.g. (Soncini-Sessa et al. (2007a,b); Castelletti and Soncini-Sessa (2007); Labadie (2004); Cloke and Pappenberger (2009); Nasir et al. (2018); Acreman et al. (2014)).

The river management objectives must usually be achieved subject to constraints on flows and water-levels. Control strategies such as Stochastic Model Predictive Control (MPC), which in addition to handling the constraints, can also incorporate the unregulated in- and out-flow forecasts and the attached uncertainties, are therefore a natural choice (Nasir (2016); Nasir et al. (2018)). In the Stochastic MPC setting, a Chance-Constrained optimisation Problem

⋆ The first and the third authors acknowledge the financial support from the Australian Research Council Linkage Project (LP130100605) and the Brescia Smart Living Project (MIUR SCN00416) respectively.

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10.1016/j.ifacol.2018.06.196

(CCP) (Cannon et al. (2009); Cinquemani et al. (2011); Primbs and Sung (2009)) is solved in a receding horizon fashion. A CCP is an optimisation problem with probabilistic constraints, which makes the problem non-solvable in general, but the scenario approach (Campi and Garatti (2008, 2011); Calafiore (2010); Carè et al. (2015)) can be employed to find approximate solutions. In the scenario approach, different scenarios of unregulated in- and out-flows, i.e. an ensemble forecast of the flows (Wang and Robertson (2011); Robertson et al. (2013); Zhao et al. (2017a)), are used in the formulation of the scenario problem, and thus it naturally accommodates the unregulated flow forecasts and their associated uncertainties. This paper provides a brief account of the scenario-based river control and the ensemble forecast of the unregulated in-flows, and discusses how the two can be merged.

The paper is organised as follows. Section 2 briefly describes a scenario-based control strategy and a modelling tool that provides ensemble forecasts for efficient river management. Section 3 discusses some common river problems where the tools are applicable, and the conclusions are given in Section 4.

2. RELEVANT TOOLS FOR EFFICIENT RIVER MANAGEMENT

In this section we describe the control and modelling tools. First, we formulate a scenario-based optimisation problem whose solution provides suitable control strategies for river management. The control strategy depends on the uncertain ensemble forecasts (scenarios) of the unregulated in-flows from the river, which is discussed in the second part of this section.

2.1 Scenario-based Control & Management of Rivers

River operations such as delivery of water to remote irrigators, water release for environmental purposes, set-point tracking of water-levels or flows along the river etc., depend on in-flows from the unregulated tributaries. Their unreliable streamflow forecasts, coupled with long time delays in the system, pose operational difficulties. Next, we present the components of a Stochastic Model Predictive Control (MPC) (Kouvaritakis and Cannon (2015)) based decision making strategy for river management that has the ability to handle the aforementioned requirements.

River Constraints: As mentioned above, the river constraints can be of different nature, e.g. some relate to the physical capacity of releases from a reservoir, some relate to operations of a hydro-electric power plant, and others are associated with environmental and recreational requirements. However, for a given river stretch between two hydraulic structures, most of these constraints can be translated into constraints on water-levels and the flow releases.

There can be multiple locations in a river stretch where water-levels are constrained and there can be multiple regulated and unregulated in- and out-flows in a given stretch. In this paper, for simplicity, we consider a basic formulation with single water-level to control and single regulated in-flow in the presence of multiple unregulated in- and out-flows, where the regulated in-flow form the decision variables of the control optimisation problem. The formulation, however, can be extended to a general river control problem, for details see (Nasir (2016); Nasir et al. (2018)). For a given river stretch, as described above, we consider the following (probabilistic) chance-constraint on the next water-level, y_{i+1}, and the current upstream flow release, Q_i, in the presence of unregulated in-flows, $Q_{u,i}$, over the finite time horizon, $i = 1, 2, \ldots, M$,

$$\begin{aligned} \mathbb{P}\{ \quad & y_{\mathrm{LL}} \leq y_{i+1}(\bar{y}_i, \bar{Q}_i, \bar{Q}_{u,i}) \leq y_{\mathrm{UL}} \quad \cap \\ & Q_{\mathrm{LL}} \leq Q_i(\bar{Q}_{u,i}) \leq Q_{\mathrm{UL}} \qquad\quad \cap \\ & \Delta Q_{\mathrm{LL}} \leq (Q_i - Q_{i-1})(\bar{Q}_{u,i}) \leq \Delta Q_{\mathrm{UL}} \quad \} \geq 1 - \epsilon, \end{aligned} \tag{1}$$

where the subscripts LL and UL indicate the lower and upper limits on the water-level, y, controlled in-flows, Q and the change in the in-flows, ΔQ, respectively. $\bar{y}_i = [y_i, y_{i-1}, y_{i-2}, \ldots, y_{i-M}]$, $\bar{Q}_i = [Q_i, Q_{i-1}, Q_{i-2}, \ldots, Q_{i-M}]$ and $\bar{Q}_{u,i} = [Q_{u,i}, Q_{u,i-1}, Q_{u,i-2}, \ldots, Q_{u,i-M}]$ are the vectors of past water-levels, and past regulated and unregulated flows, on which the next water-level is dependent. Also, the decision variable, Q_i, is a function of $\bar{Q}_{u,i}$, and hence in the decision making process, we aim to optimise over control policies rather than control values, as it generally leads to handle uncertainties and constraints better, see e.g. (Mayne et al. (2000); Mesbah (2016); Lofberg (2003); Goulart et al. (2006)). The probability measure $\mathbb{P}$ is with respect to the unregulated in-flows, Q_u, which is assumed available, and the probability level, ϵ, is user chosen. Also, we assume that the dynamical equations that govern flows and water-levels enforce a convex constraint in the control policy space. This assumption is satisfied by most of the models proposed in the literature of river modelling for control purposes, see e.g. (Foo et al. (2012); Nasir and Weyer (2016); Young et al. (2007)).

River Management Problem: In a Stochastic MPC setting, a Chance-Constrained optimisation Problem (CCP) (Cannon et al. (2009); Cinquemani et al. (2011); Primbs and Sung (2009)) is solved at every time step. The optimisation problem considers a finite future time horizon in decision making. However, only the decision obtained for the first time step is applied. The objective function considered in the optimisation problem is as follows,

$$\begin{aligned} J = \mathbb{E} \Bigg[& \sum_{i=k+1}^{k+M} \alpha_{1,i}(y_i - y_{\mathrm{des}})^2 \\ & + \sum_{i=k}^{k+M-1} \left(\alpha_{2,i}(Q_i - Q_{i-1})^2 + \alpha_{3,i} Q_i^2 \right) \Bigg], \end{aligned} \tag{2}$$

where y_{des} is a desired water-level, and $\alpha_{1,i}$, $\alpha_{2,i}$ and $\alpha_{3,i}$ are user-chosen weights. Again, the expectation $\mathbb{E}$ is with respect to the unregulated in-flows Q_u, on which the water-level, y, and the in-flow, Q (via the control policy), are dependent. The objective function has three components, and the control policies, $Q_k, Q_{k+1}, \ldots, Q_{k+M-1}$, will seek to minimise

- Deviation of water-level, y, from a desired level, y_{des}.
- Controlled releases, Q, to avoid waste of water.
- Change in controlled releases, ΔQ, to avoid abrupt changes.

Together the objective function in (2) and the constraints in (1) define the following CCP,

$$\min_{Q_k, Q_{k+1}, \ldots, Q_{k+M-1}} \quad J \tag{3}$$

subject to

$$\{\text{System dynamics is satisfied}\},$$
$$\text{and}$$
$$\mathbb{P}\{ \quad y_{\text{LL}} \leq y_{i+1}(\bar{y}_i, \bar{Q}_i, \bar{Q}_{u,i}) \leq y_{\text{UL}} \quad \cap$$
$$Q_{\text{LL}} \leq Q_i(\bar{Q}_{u,i}) \leq Q_{\text{UL}} \quad \cap$$
$$\Delta Q_{\text{LL}} \leq (Q_i - Q_{i-1})(\bar{Q}_{u,i}) \leq \Delta Q_{\text{UL}} \quad \} \geq 1 - \epsilon,$$
$$i = k, k+1, \ldots, k+M-1.$$

Problem (3) can be solved in a Stochastic MPC setting. However, generally speaking, a CCP is non-convex with respect to the decision policies $(Q_k, Q_{k+1}, \ldots, Q_{k+M-1})$, even if the deterministic constraints are convex. There are randomised strategies available in the literature that can provide computationally tractable approximate solution to CCPs. The scenario approach (Campi and Garatti (2008, 2011); Campi et al. (2009); Calafiore (2010); Carè et al. (2015)) is popular because of its simplicity, and it has been applied to river control problems, see e.g. (Nasir (2016); Nasir et al. (2018, 2016)).

Scenario-based River Management Problem: In the scenario approach (Campi and Garatti (2008, 2011); Campi et al. (2009); Calafiore (2010); Carè et al. (2015)), we find an approximate solution to a given CCP. We generate N_r independent realisations of the uncertain variable, e.g. N_r time series of the unregulated in-flow, Q_u, according to a given probability distribution, and replace the chance constraint in the CCP with N_r constraints, each having one of the N_r realisations of the time series. E.g. '$\mathbb{P}\{y_{\text{LL}} \leq y_{i+1}(Q_i, Q_{u,i}) \leq y_{\text{UL}}\} \geq 1 - \epsilon$' will be replaced with '$y_{\text{LL}} \leq y_{i+1}(Q_i, Q_{u,i}^{(j)}) \leq y_{\text{UL}}$', for $j = 1, 2, \ldots, N_r$. The obtained problem is known as the scenario problem, and it is convex, provided the original constraints are convex with respect to the optimisation variables. The scenario problem provides with high confidence a feasible solution to the CCP, provided N_r is chosen large enough. A sufficiently large value of N_r can be found by using the scenario theorem which states that (Campi and Garatti (2008)): "If N_r satisfies

$$\sum_{m=0}^{d-1} \binom{N_r}{m} \epsilon^m (1-\epsilon)^{N_r - m} \leq \beta, \tag{4}$$

where $\epsilon \in (0, 1)$ is the allowed violation probability of the chance-constraint, $\beta \in (0, 1)$ is a user chosen confidence parameter and d is the number of optimisation variables, then the scenario solution is feasible for the chance-constraint with confidence at least $1 - \beta$".

The confidence parameter β can be explained as follows (Campi and Garatti (2008)): It cannot be guaranteed that the scenario solution is always feasible for the CCP in Problem (3), because it might happen that the N_r extracted realisations are not representative enough. However, if the criterion in (4) is met, then the probability of such an event is less than β, and the feasibility of the scenario solution is ensured with confidence $1 - \beta$. Typically the confidence parameter, β, is chosen as a small number, e.g. 10^{-6}.

With the application of the scenario approach we replace Problem (3) with the following scenario problem,

$$\min_{Q_k, Q_{k+1}, \ldots, Q_{k+M-1}} \quad J \tag{5}$$

subject to

$$\{\text{System dynamics is satisfied}\},$$
$$\text{and}$$
$$y_{\text{LL}} \leq y_{i+1}(\bar{y}_i, \bar{Q}_i, \bar{Q}_{u,i}^{(j)}) \leq y_{\text{UL}},$$
$$Q_{\text{LL}} \leq Q_i(\bar{Q}_{u,i}^{(j)}) \leq Q_{\text{UL}},$$
$$\Delta Q_{\text{LL}} \leq (Q_i - Q_{i-1})(\bar{Q}_{u,i}^{(j)}) \leq \Delta Q_{\text{UL}},$$
$$i = k, k+1, \ldots, k+M-1,$$
$$j = 1, 2, \ldots, N_r.$$

Problem (S-CCP) is convex with respect to the decision variables and is solvable. The literature provides various modelling techniques which provide ensemble forecasts (scenarios) of the unregulated in-flows from tributaries, see e.g. (Wang and Robertson (2011); Robertson et al. (2013); Bennett et al. (2016)). Therefore, these modelling techniques form a natural fit to the above scenario-based river management problem. In the next sub-section, we briefly describe the background of the ensemble forecast of unregulated in-flows.

2.2 Ensemble Forecast of Unregulated In-flows

In this section we briefly discuss how hydrological models describe unregulated in-flows and provide their ensemble forecasts.

Hydrological Modelling: The unregulated in-flows, Q_u, are usually forecasted using catchment hydrological models (Cloke and Pappenberger (2009); Bennett et al. (2016)). A hydrological model accounts for various influencing factors in the catchment, and it formulates the rainfall-runoff relationship (Duan and Sorooshian (1992)). The relationship is described between precipitation, p, and the in-flows, Q_u, because precipitation is the major determinant of the catchment flows. Moreover, these flows are also affected by the catchment features, such as land use, land cover, soil texture, wetlands, lakes, etc. A hydrological model can be simply conceptualised as (Bennett et al. (2016)),

$$[Q_{u,k}, Q_{u,k+1}, \ldots, Q_{u,k+M-1}] = H(\underbrace{\ldots, p_{k-2}, p_{k-1}}_{\text{antecedent}}, p_k, \underbrace{p_{k+1}, p_{k+2}, \ldots, p_{k+M-1}}_{\text{future}}). \tag{6}$$

where k provides the time index. The antecedent and future precipitations are discussed below.

H, in (6), depends on physical variables and parameters. The physical variables account for the catchment wetness/dryness, including soil moisture and groundwater storage. These variables can be initialised by hydrological simulations, for details see e.g. (Bennett et al. (2016)). The parameters refine the rainfall-runoff relationship, which facilitates the separation of the precipitation into streamflow, groundwater flow and flow through the soil. These parameters can be calibrated by optimisation routines, for details see e.g. (Duan and Sorooshian (1992)).

In hydro-climatic forecasting, as shown in (6), there are two components of precipitation: 1) antecedent precipi-

tation, which determines the catchment wetness/dryness. It can be obtained from observations at rain gauges or inferred from radar images (Cloke and Pappenberger (2009)); and 2) future precipitation, which plays a crucial part in determining future flows, but it is unknown. Regional and global climate models (RCMs/GCMs) (Robertson et al. (2013); Zhao et al. (2017a)) produce precipitation forecasts at hourly, daily and monthly rates. However, when such forecasts are unavailable, the historical precipitation scenarios can be employed to predict future precipitation. Based on the observed and the forecasted precipitation, streamflow forecasts (i.e. the unregulated in-flow, Q_u, in the setup of this paper) can be generated by the hydrological models. These forecasts can be further processed to correct bias and to improve reliability (Cloke and Pappenberger (2009); Bennett et al. (2016)). The unregulated in-flows can also be forecasted as an ensemble, which is discussed next.

Ensemble Forecast and its Attributes: In hydro-climatic forecasting, ensemble forecasts are very useful (Wang and Robertson (2011); Robertson et al. (2013); Zhao et al. (2017a)). The ensemble forecast is generated from an hydrological model and it contains multiple flow scenarios which provides a way to characterise the underlying uncertainty in the flow (i.e. in the unregulated in-flows). The uncertainty originates from the input precipitation, the structure and parameters of the hydrological model. In the forecasting process, the uncertainties from these different sources propagate, for details see (Clark et al. (2008); Vrugt et al. (2009)). Monte Carlo simulations are employed to account for the different kinds of uncertainties and generate the ensemble forecasts (Bennett et al. (2016); Clark et al. (2008)). In particular, Markov Chain Monte Carlo (MCMC) algorithm is widely used in the literature, e.g. see (Vrugt et al. (2009))

The correspondence between ensemble forecasts and the corresponding observations can be verified by statistical metrics and diagnostic plots (Wang and Robertson (2011); Bennett et al. (2016)). The important attributes of the ensemble forecasts are *bias*, *reliability* and *skill*. These attributes closely relate to the value of the ensemble forecasts in water management. For more details on the attributes of a good forecast, see (Murphy (1993)). The value of ensemble forecasts in reservoir operations has also been investigated in (Turner et al. (2017)).

The ensemble forecast models account for the underlying probability distribution of future flows (Cloke and Pappenberger (2009); Wang and Robertson (2011)), from which one can draw as many scenarios as one requires for analyses, e.g., at the beginning of every month, 1000 streamflow scenarios are generated at the Australian Bureau of Meteorology. This facilitates the scenario-based Stochastic MPC strategy in accommodating a sufficient number of forecasted scenarios, N_r (see (4)), of the unregulated flows.

3. EXAMPLES OF RIVER MANAGEMENT

In this section, we highlight a few applications that can be targeted with the tools described in the previous section.

3.1 Flood Avoidance

Like several other systems, rivers have normal control operations and some operations related to risk mitigation. The latter operations often include flood avoidance. Here we briefly describe the approach in (Nasir et al. (2018)) to the flood avoidance problem.

The flood avoidance can be accommodated in two ways. First, one can formulate a flood risk related penalty criterion, and append it to the existing objective function of the river management problem, see (2). Second, a suitable constraint related to flooding can be appended to the existing constraints of the river management problem, see (1). The former approach can be conservative with an overemphasis on avoiding risks, even when there are no evident risks. The latter approach, however, keeps an eye on the flood related constraint and signals if there is a possibility of flooding. In such circumstances, the satisfaction of risk mitigation constraints can be prioritised over the normal operations and conservatism is avoided.

In (Nasir et al. (2018, 2016)), the following chance-constraint on the water-level, y_i, was used,

$$\mathbb{P}\{ \quad y_{i+1}(Q_i, Q_{u,i}) \leq y_{\mathrm{FL}} \quad \} \geq 1 - \epsilon_f, \tag{7}$$

where the subscript FL represents a flood limit. The y_{FL} is higher than the y_{UL} in (1), and the crossing of this limit indicates flooding risks. The allowed violation probability $\epsilon_f \ll \epsilon$, i.e. the satisfaction of the flood avoidance constraint is required with higher probabilistic guarantees compared to the guarantees on the normal operations. With the addition of the constraints in (7) to Problem (3), the river management includes flood avoidance, and it becomes a Multiple Chance-Constrained optimisation Problem (M-CCP) (Schildbach et al. (2013)). Again, there are randomised approaches, available in the literature, that can utilise ensemble forecasts to find approximate solutions to an M-CCP, e.g. see (Zhang et al. (2013); Schildbach et al. (2013)). However, due to the small ϵ_f values, the scenario approach (4) requires a large number of scenarios in the ensemble forecast, and thus causes a computational burden. In (Nasir et al. (2018)), the authors proposed a computationally efficient *Optimisation, Testing and Improvement algorithm*, especially targeted for flood avoidance problems. The algorithm finds an approximate solution to the M-CCP as follows: The solution to Problem (3) is tested against the flood avoidance constraint (7) using new scenarios, and improvements are only made to the solution, if the test fails. This approach reduces the computational burden. For further details, see (Nasir et al. (2018)).

3.2 Long-term River Management

Ensemble forecasts of unregulated in-flows to a river are available on daily, monthly and seasonal time scales, e.g. for short-term management see (Cloke and Pappenberger (2009)) and for long-term management see (Bennett et al. (2016); Wang and Robertson (2011)). In particular, the long-term management provides guidance, e.g. carry-over storage from the current month to the next month, to short-term decision making, e.g. daily releases in the current month, see (Zhao and Zhao (2014)). The long-term management is also necessary for large river basins, as the

transport losses to evaporation are large for such basins, e.g. see (Acreman et al. (2014)). In long-term forecasting, the future precipitation in the hydrological model (see (6)) plays a major role in determining the future flows, and as a result, the uncertainty in the future precipitation dominates the long-term flow forecasts.

With the availability of the tools providing river description and ensemble forecasts of unregulated in-flows, the long-term river management can be based on the scenario-based Stochastic MPC framework in Section 2.1. The objectives and the constraints in Problems (3) & (5) can be modified accordingly. E.g., in the objective function (2), the first term can be replaced with a comparison of a flow, Q_i (volume per day), at a particular location at the downstream end, with a desired flow Q_{des} (replacing y_i with Q_i and y_{des} with Q_{des} in (2)). With that in place, the mathematical description of the flow, Q_i, and its relevant limits must also be added to the constraints in (1).

3.3 Management Related to Environmental Aspects

Environmental aspects of river management is receiving increased attention, see e.g. (MDBA (2014)). The river flow should be kept high enough to ensure a certain amount of spillage to wetlands, flood plains and forests adjacent to rivers. A hindrance to such actions can cause adverse effects on the environment, e.g., without a proper spillage, river forests develop toxic water, which is dangerous to the lives in flowing rivers and ultimately to humans.

To ensure the safety of wetlands, river spillage can be accommodated in both short-term and long-term river managements. The river constraints in (1) can be modified for a specific season, where such spillages are less costly, more likely and safe. Some flow peaks, e.g. from an unregulated river, can be used and/or topped up with additional releases from a reservoir, depending on the requirements of the wetland. The technical challenge here is to forecast the timing and amplitude of such flow peaks with good accuracy to match it with the releases from a reservoir. A specific models for high flow range can also be used for such tasks. Furthermore, models for overbank flow can be sought too (Zhao et al. (2017b)). With such models and constraints in place, the scenario-based river management (Problems (3) & (5)) can conveniently accommodate and address the issues related to environmental aspects.

4. CONCLUSIONS

To ensure efficient river management, forecasts of unregulated flows, along with their uncertainties, should be incorporated in the management process. This paper proposed a way to combine tools that provide ensemble forecast (scenarios) of unregulated flows with the Stochastic MPC based control strategy that can accommodate those scenarios in the control and management process. The paper also discussed a few river problems, where such a procedure is applicable.

REFERENCES

Acreman, M., Arthington, A., Colloff, M., Couch, C., Crossman, N., Dyer, F., Overton, I., Pollino, C., Stewardson, M., and Young, W. (2014). Environmental flows for natural, hybrid, and novel riverine ecosystems in a changing world. *Frontiers in Ecology and the Environment*, 12(8), 466–473.

Bennett, J., Wang, Q., Li, M., Robertson, D., and Schepen, A. (2016). Reliable long-range ensemble streamflow forecasts: Combining calibrated climate forecasts with a conceptual runoff model and a staged error model. *Water Resources Research*, 52(10), 8238–8259.

Calafiore, G. (2010). Random convex programs: Dealing with the non-existing solution nuisance. In *49th Conference on Decision and Control (CDC)*, 1939–1944. IEEE.

Campi, M. and Garatti, S. (2008). The exact feasibility of randomized solutions of uncertain convex programs. *SIAM Journal on Optimization*, 19(3), 1211–1230.

Campi, M. and Garatti, S. (2011). A sampling-and-discarding approach to chance-constrained optimization: feasibility and optimality. *Journal of Optimization Theory and Applications*, 148(2), 257–280.

Campi, M., Garatti, S., and Prandini, M. (2009). The scenario approach for systems and control design. *Annual Reviews in Control*, 33(2), 149–157.

Cannon, M., Kouvaritakis, B., and Wu, X. (2009). Probabilistic constrained MPC for multiplicative and additive stochastic uncertainty. *IEEE Transactions on Automatic Control*, 54(7), 1626–1632.

Cantoni, M., Weyer, E., Li, Y., Ooi, S., Mareels, I., and Ryan, M. (2007). Control of large-scale irrigation networks. *Proceedings of the IEEE*, 95(1), 75–91.

Carè, A., Garatti, S., and Campi, M. (2015). Scenario min-max optimization and the risk of empirical costs. *SIAM Journal on Optimization*, 25(4), 2061–2080.

Castelletti, A. and Soncini-Sessa, R. (2007). Coupling real-time control and socio-economic issues in participatory river basin planning. *Environmental Modelling & Software*, 22(8), 1114–1128.

Cinquemani, E., Agarwal, M., Chatterjee, D., and Lygeros, J. (2011). Convexity and convex approximations of discrete-time stochastic control problems with constraints. *Automatica*, 47(9), 2082–2087.

Clark, M., Slater, A., Rupp, D., Woods, R., Vrugt, J., Gupta, H., Wagener, T., and Hay, L. (2008). Framework for Understanding Structural Errors (FUSE): A modular framework to diagnose differences between hydrological models. *Water Resources Research*, 44(12).

Cloke, H. and Pappenberger, F. (2009). Ensemble flood forecasting: a review. *Journal of Hydrology*, 375(3), 613–626.

Corani, G. and Guariso, G. (2005). Coupling fuzzy modeling and neural networks for river flood prediction. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 35(3), 382–390.

Duan, Q. and Sorooshian, S.and Gupta, V. (1992). Effective and efficient global optimization for conceptual rainfall-runoff models. *Water resources research*, 28(4), 1015–1031.

Foo, M., Ooi, S., and Weyer, E. (2012). Modelling of rivers for control design. *In System Identification, Environmental Modelling, and Control System Design*, 423–447.

Goulart, P., Kerrigan, E., and Maciejowski, J. (2006). Optimization over state feedback policies for robust control with constraints. *Automatica*, 42(4), 523–533.

Kouvaritakis, B. and Cannon, M. (2015). Stochastic model predictive control. *Encyclopedia of Systems and Control*, 1350–1357.

Labadie, J. (2004). Optimal operation of multireservoir systems: state-of-the-art review. *Journal of water resources planning and management*, 130(2), 93–111.

Litrico, X. (2002). Robust IMC flow control of SIMO dam-river open-channel systems. *IEEE Transactions on Control Systems Technology*, 10(3), 432–437.

Litrico, X., Fromion, V., Baume, J.P., Arranja, C., and Rijo, M. (2005). Experimental validation of a methodology to control irrigation canals based on Saint Venant equations. *Control Engineering Practice*, 13(11), 1425–1437.

Lofberg, J. (2003). Approximations of closed-loop minimax MPC. In *42nd Conference on Decision and Control (CDC)*, volume 2, 1438–1442. IEEE.

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

MDBA (2014). Basin-wide environmental watering strategy. *Murray-Darling Basin Authority, Canberra*, (Publication No 20/14, URL: https://www.mdba.gov.au/sites/default/files/pubs/Final-BWS-Nov14_0816.pdf).

Mesbah, A. (2016). Stochastic model predictive control: An overview and perspectives for future research. *IEEE Control Systems Magazine*, 36(6), 30–44.

Murphy, A. (1993). What is a good forecast? An essay on the nature of goodness in weather forecasting. *Weather and forecasting*, 8(2), 281–293.

Nasir, H. (2016). *System identification and control of rivers*. PhD thesis, The University of Melbourne.

Nasir, H., Carè, A., and Weyer, E. (2018). A randomised approach to control problems with two chance-constraints with application to river control. *IEEE Transactions on Control Systems Technology (to appear)*.

Nasir, H., Garatti, S., and Weyer, E. (2016). Scenario based stochastic MPC schemes for rivers with feasibility assurance. In *European Control Conference (ECC)*, 1928–1933.

Nasir, H. and Muhammad, A. (2011). Control of very-large scale irrigation networks: A CPS approach in a developing world setting. In *Proceedings of IFAC World Congress, Milan, Italy*.

Nasir, H. and Weyer, E. (2016). System identification of the upper part of Murray River. *Control Engineering Practice*, 52, 70–92.

Pianosi, F., Castelletti, A., and Lovera, M. (2012). Identification of a flow routing model for the Red River network. In *IFAC Symposium on System Identification*, volume 16, 1037–1042.

Primbs, J. and Sung, C. (2009). Stochastic receding horizon control of constrained linear systems with state and control multiplicative noise. *Automatic Control, IEEE Transactions on*, 54(2), 221–230.

Robertson, D., Shrestha, D., and Wang, Q. (2013). Post-processing rainfall forecasts from numerical weather prediction models for short-term streamflow forecasting. *Hydrology and Earth System Sciences*, 17(9), 3587.

Schildbach, G., Fagiano, L., and Morari, M. (2013). Randomized solutions to convex programs with multiple chance constraints. *SIAM Journal on Optimization*, 23(4), 2479–2501.

Setz, C., Heinrich, A., Rostalski, P., Papafotiou, G., and Morari, M. (2008). Application of Model Predictive Control to a cascade of river power plants. In *Proceedings of the IFAC World Congress*.

Soncini-Sessa, R., Cellina, F., Pianosi, F., and Weber, E. (2007a). *Integrated and participatory water resources management: Practice*. Elsevier Science Limited.

Soncini-Sessa, R., Weber, E., and Castelletti, A. (2007b). *Integrated and participatory water resources management: Theory*. Elsevier Science Limited.

Turner, S., Bennett, J., Robertson, D., and Galelli, S. (2017). Complex relationship between seasonal streamflow forecast skill and value in reservoir operations. *Hydrology and Earth System Sciences*, 21(9), 4841.

Van Overloop, P., Schuurmans, J., Brouwer, R., and Burt, C.M. (2005). Multiple-model optimization of Proportional Integral controllers on canals. *Journal of irrigation and drainage engineering*, 131(2), 190–196.

Vrugt, J., Ter Braak, C., Diks, C., Robinson, B., Hyman, J., and Higdon, D. (2009). Accelerating Markov chain Monte Carlo simulation by differential evolution with self-adaptive randomized subspace sampling. *International Journal of Nonlinear Sciences and Numerical Simulation*, 10(3), 273–290.

Wang, Q. and Robertson, D. (2011). Multisite probabilistic forecasting of seasonal flows for streams with zero value occurrences. *Water Resources Research*, 47(2).

Weyer, E. (2008). Control of irrigation channels. *IEEE Transactions on Control Systems Technology*, 16(4), 664–675. doi:10.1109/TCST.2007.912122.

Young, P., Castelletti, A., and Pianosi, F. (2007). The data-based mechanistic approach in hydrological modelling. *Topics on System Analysis and Integrated Water Resource Management*, 27–48.

Zhang, X., Margellos, K., Goulart, P., and Lygeros, J. (2013). Stochastic model predictive control using a combination of randomized and robust optimization. In *52nd Annual Conference on Decision and Control (CDC)*, 7740–7745. IEEE.

Zhao, T., Bennett, J., Wang, Q., Schepen, A., Wood, A., Robertson, D., and Ramos, M. (2017a). How suitable is quantile mapping for postprocessing gcm precipitation forecasts? *Journal of Climate*, 30(9), 3185–3196.

Zhao, T., Shao, Q., and Zhang, Y. (2017b). Deriving flood-mediated connectivity between river channels and floodplains: Data-driven approaches. *Scientific Reports*, 7.

Zhao, T. and Zhao, J. (2014). Joint and respective effects of long-and short-term forecast uncertainties on reservoir operations. *Journal of hydrology*, 517, 83–94.