Optimal operation of the multi-reservoir system in the Seine River basin using deterministic and ensemble forecasts

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Abstract

We investigate the improvement of the operation of a four-reservoir system in the Seine River basin, France, by use of deterministic and ensemble weather forecasts and real-time control. In the current management, each reservoir is operated independently from the others and following prescribed rule-curves, designed to reduce floods and sustain low-flows under the historical hydrological conditions. However, this management system is inefficient when inflows are significantly different from their seasonal average and may become even more inadequate to cope with the predicted increase in extreme events induced by climate change. In this work, we develop and test a centralized real-time control system to improve reservoirs operation by exploiting numerical weather forecasts that are becoming increasingly available. The proposed management system implements a well-established optimization technique, Model Predictive Control (MPC) and its recently modified version that can incorporate uncertainties, Tree-Based Model Predictive Control (TB-MPC), to account for deterministic and ensemble forecasts respectively. The management system is assessed by simulation over historical events and compared to the "no-forecasts" strategy based on rule-curves. Simulation results show that the proposed real-time control system largely outperforms the "no-forecasts" management strategy, and that explicitly considering forecasts uncertainty through ensembles can compensate for the loss in performance due to forecasts inaccuracy.

Introduction

The goal of this paper is to present the development of a real-time control system to support reservoir management using deterministic and ensemble weather forecasts in the Seine River basin in France. The reservoir system includes four reservoirs upstream of Paris, and is operated with the objective of reducing floods and supporting low-flows in a large area of high economic value. The current management of the reservoirs is reactive and decentralized and it is based on rule-curves that were designed from time series of historical inflows. Therefore its efficiency is limited when inflows are significantly different from their seasonal average. Moreover, Dorchies et al. (2014) have shown that it might be largely inadequate to cope with the projected increase in frequency and intensity of extreme events. As suggested by Dorchies et al. (2014), the current management efficiency could be improved by a centralized and anticipatory management strategy. In centralized management, operational decisions at each location are optimized simultaneously considering the overall response of the multi-reservoir system, potentially leading to a strong increase in the system performances (see for instance Anghileri et al., 2013; Giuliani and Castelletti, 2013; Marques and Tilmant, 2013). In anticipatory water management, numerical weather forecasts are combined with simulation-optimization models to take operational actions before an event occurs (e.g. van Andel et al., 2012; Wang et al., 2014).

Following these ideas, the present study investigates the use of a centralized real-time management system that implements Model Predictive Control (MPC, Mayne et al., 2000) and Tree-Based Model Predictive Control (TB-MPC, Raso et al., 2014) using deterministic and ensemble weather forecasts respectively. MPC is a well-established optimal control technique that has already shown its efficiency for set-point control of open-water systems, especially irrigation and drainage channels (e.g. Van Overloop, 2006) and has gained increasing attention in the reservoir operation literature in the last years (e.g. Anand et al., 2011; Breckpot et al. 2013a; Breckpot et al., 2013b; Galelli et al., 2014; Schwanenberg et al., 2014; Tian et al., 2015). In MPC, optimal control decisions are computed at each decision time-step, e.g. daily or weekly, by optimization of the simulated system performances over a prediction horizon of days or weeks. Since the simulation model can be initialized by observed hydrological conditions and forced by weather forecasts available at the time of decision, MPC provides a formal approach to fully exploit real-time information, both observations and forecasts, for water systems operation. Breckpot et al. (2013a) and Galelli et al. (2014) present recent applications of MPC to reservoir operation. In these works, however, weather forecasts are not used and MPC can anticipate the system response only over a short prediction horizon (i.e. some hours) by exploiting the delay in the watershed input-output dynamics. In another study, Breckpot et al. (2013b) show that MPC outperforms the current reactive management strategy for flood control of the Demer River in Belgium when using historical rainfall data as predictions, however the robustness of MPC against uncertainty on the weather predictions is not examined. The main limitation of the deterministic approach is that its performances quickly deteriorate if forecasts are not accurate. Previous studies demonstrate that the loss in performances due to inaccurate forecasts can be partially compensated if forecast uncertainty is explicitly considered in the optimization process. For instance, Pianosi and Ravazzani (2010) apply an MPC-like approach based on Stochastic Dynamic Programming to a single reservoir system, and show the benefits of considering predictive uncertainty of rainfall-runoff models, both empirical and physical-based, for flood control. Kim et al. (2007) use Sampling Stochastic Dynamic Programming with ensemble streamflow predictions for the operation of a multi-reservoir system and show the improvements in system performance by explicitly including inflow uncertainty via ensemble forecasts. Roulin (2007) shows the improvement of a flood early warning system by using ensemble forecasts instead of deterministic ones in a simple static cost-loss decision model for two test catchments. Boucher et al. (2011) compare the use of deterministic and ensemble hydrological forecasts in a two-stage decision tree for the operation of a hydropower system, and show that the two types of forecasts products bring similar good performances. Recently, Raso et al. (2014) presented a novel technique to handle ensemble forecasts in MPC optimization, named Tree-Based MPC (TB-MPC). While MPC searches for the trajectory of decisions that proves optimal under the deterministic trajectory of input forecasts, TB-MPC searches for the decision tree that optimizes the system response along the different paths defined by the forecast ensemble members.

In this study, we developed a MPC and TB-MPC management system for the four reservoirs in the Seine River basin and tested it using real weather forecasts data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF), and a semi-distributed hydrological model. Since weather forecasts can be exploited to cope with short-term events only, the long-term objectives of the reservoir management are accounted for by using penalty functions over the reservoir storages reached at the end of the prediction horizon. As such penalty functions are defined based on deviations from the reservoirs' rule-curves, the proposed (TB-)MPC management system can be viewed as a means to incorporate weather forecasts into the current management structure, which may increase its acceptability for decision-makers (Gong et al., 2010). We simulate the proposed (TB-)MPC system over historical events and compare it to the uncoordinated "no-forecast" management strategy based on rule-curves, assessing the loss in performance due to forecasts inaccuracy and the benefits of considering forecasts uncertainty.

The Seine River basin

The study area

The system considered in this study is the Seine River basin upstream of Paris, France (Fig. 1). The study area covers about 43,824 km^2 and is characterized by high water demand and high vulnerability to floods, especially in the Paris urban area. In order to reduce floods and support water supply in low-flow periods, four reservoirs were constructed between the 1950s and the 1990s. The four reservoirs, named Aube, Seine, Pannecière and Marne, have a total capacity of 810 hm^3 and are managed by Seine Grands Lacs (SGL), a French public establishment. While the Pannecière reservoir was created by damming the Yonne River, a tributary of the Seine, the other three are bank-side reservoirs. Table 1 reports the capacity of each reservoir and of its inlet and outlet channels.

Currently, each reservoir is operated independently from the others following a Rule-Curve (RC) that sets the target reservoir volume for each day of the year. The RCs are designed in order to store water during the high-flow season (from November to June), while maintaining adequate flood control volumes, and to sustain low-flows during the dry season (from July to October). The reservoirs operation must also respect some constraints on the reservoir inflows and outflows. Specifically, water withdrawals are limited by minimum environmental flow requirements (called *reserved flows*) on downstream rivers, while the river flow downstream from the outlet cannot exceed a maximum value (called *reference flow*) designed to prevent downstream floods (Table 1).

The performances of the reservoir operation can be evaluated by considering the frequency with which flow thresholds at 9 strategic gauging stations - or “monitoring stations” from now onwards - are respected (Dorchies et al. 2014). These are four low-flow thresholds (vigilance, alert, reinforced alert and crisis) in correspondence to different levels of restrictions to water use (Table 2), and three high-flow thresholds (vigilance, alert and crisis) that are used among other information by the French flood forecasting service for defining three flood warnings (bankfull discharge, frequently flooded areas, and exceptional flood event; see Table 2).

Data used

Meteorological and hydrological data

Meteorological data (daily precipitation and temperature) were obtained from the SAFRAN database of Météo-France (Vidal et al., 2010). The original spatial resolution was 8 km x 8 km, therefore data had to be aggregated to the sub-basin scale of the semi-distributed hydrological model (see next section). Daily potential evapotranspiration time-series were calculated by the Penman-Monteith formula (Penman, 1948).

Daily flows at various river sections were extracted from the data-base of "naturalized" flows (i.e., reconstructed flows obtained from observations by removing the influence of reservoir operation) provided by SGL (Hydratec, 2011).

Reservoirs data

Reservoirs data were provided by SGL, including: maximum and minimum storages; capacity of the inlet/outlet channels; rule-curves; minimum environmental flows (*reserved flows*) for downstream river reaches and maximum flows downstream from the outlets (*reference flows*); high and low flow thresholds at downstream strategic gauging stations.

Weather forecasts

Precipitation forecasts come from the European Centre for Medium-Range Weather Forecasts (ECMWF) ensemble prediction system (Buizza et al., 1999). Ensemble forecasts (hereafter, EFs) are composed of 50 perturbed members and one 'control' member that is initialized with the same initial condition as the deterministic forecast (DF). Ensemble forecasts were available from March 11th, 2005 to October 1st, 2008, with a maximum lead time of 9 days and at daily temporal resolution. ECMWF EFs can also be provided at 6h time step, but for our study the daily resolution was sufficient, given the daily time step of the hydrological model. The original spatial resolution is of 55 x 55 km (0.5° x 0.5° lat/lon), but one value of areal rainfall was estimated for the entire watershed as the average over the 15 grid points falling within the watershed (43,824 km^2) weighted by the percentage of coverage. Given that the watershed is characterized by slow dynamics with high spatial correlation at the daily time step (oceanic weather type), we expect spatial averaging of rainfall forecasts to have negligible impact on the results. Table 3 reports the EF mean, spread (i.e. standard deviation), and accuracy (i.e Root Mean Square Error of the EFs mean) at lead-time from 1 to 9 days. Notice that the EFs spread slightly increases with the lead-time, while the accuracy remains fairly constant.

Models and methods

In this work we compare two management strategies:

A) The uncoordinated management system that is currently being employed, which relies on the use of rule-curves and does not consider weather forecast ("no-forecast operation" from now onwards);

B) A centralized and anticipatory operation that relies on the use of real-time optimization and exploit the available weather forecast ("operation-with-forecast"). In the following, we will further distinguish and compare three options, according to the forecast type:

i. "Perfect forecast": observed rainfall and temperature data are used in place of forecasts. The goal is to evaluate the upper bound of the reservoir operation performance in the ideal case that weather forecasts were not affected by any type of uncertainty.

ii. "Deterministic forecast" provided by the ECMWF for daily rainfall (lead time of 9 days) and the seasonal mean over historical records for the evapotranspiration.

iii. “Ensemble Forecasts” provided by the ECMWF for daily rainfall (lead time of 9 days) and the seasonal mean for the evapotranspiration.

To compare the different management methods by model simulation, an integrated model of the physical and decision system was developed. The hydrological-hydraulic model of the physical system reproduces the rainfall-runoff process, the reservoirs dynamics, and flow-routing. The decision model mimics the daily operation of the system, and thus provides the inflow/outflow decisions to be applied at the inlet(s) and outlet of each reservoir. Fig. 2 illustrates the information fluxes in the two cases. In the “no-forecast operation” (left), decisions only depend on the reservoir storage (and day of the year), through the application of RCs, and on river flows upstream/downstream of the reservoirs, through the implementation of reserved/reference flow constraints. In the “operation-with-forecast”, instead, decisions at each day are computed by a simulation-optimization process that evaluates and optimizes the system response to decisions under the forecasts scenario. The components of the integrated simulation model are described below.

Hydrological and hydraulic model

The hydrological and hydraulic model of the Seine River basin is the semi-distributed conceptual TGR model (Munier, 2009), already used for this basin by Dorchies et al. (2014) and Munier et al. (2014). The TGR model couples the hydrological lumped rainfall-runoff GR4J model (Perrin et al., 2003) at daily time step with a simplified hydraulic model that takes into account flow propagation and attenuation, withdrawals, lateral inflows from runoff and point inflows from the reservoirs. In the TGR model, calculations are made at the scale of each sub-basin located between two gauging stations. The Seine River basin is divided into 25 sub-basins having as outlets the 25 gauging stations upstream of Paris (Fig. 1). The four reservoirs were included into the TGR model by defining new sub-basins at the connection points between river and inlet/outlet channels. The inputs of the reservoir models are the daily inlet and outlet flows, which constitute the decision variables calculated on the basis of the RCs in the "no-forecast operation" and otherwise obtained by optimization. The TGR model was calibrated using the time-series of "naturalized" flows over the period 1961-2009. More details about the model calibration and validation are given in Dorchies et al. (2014).

Operation model

The operation model reproduces the behavior of the reservoirs managers to provide the daily decisions of inflows and outflows from each reservoir. In the "no-forecast operation" case, the model implements the application of the RCs and the constraints on maximum inflows and outflows reported in Table 1. In the "operation-with-forecast" case, it implements a real-time optimization strategy, called Model Predictive Control (MPC) strategy. MPC uses a dynamic model (in our case the hydraulic model) to predict the system behavior in response to the control actions over a finite horizon, called *prediction horizon*. The model takes as the initial state the current measured or estimated state of the system and as inputs the forecasts of the disturbances that act on the system. MPC selects the control trajectory that provides the best predicted behavior over the prediction horizon (Maciejowski, 2002). Thanks to the use of the dynamical model of the system and of the forecasts, the management becomes *proactive,* acting in advance to deal with the future expected problems caused by the disturbances. At each time-step, MPC provides the optimal control sequence over the entire prediction horizon. However, only the first control value of this sequence is actually applied to the system, and at the next time-step, the same optimization procedure is repeated using updated forecasts over a prediction horizon shifted one-step-ahead (*receding horizon principle).* Selection of the control sequence is based on minimization/maximization of an objective function that formalizes the management goals (for example to minimize flood costs) while respecting some constraints (for example the capacity of the diversion channels). When using deterministic forecasts, the objective function takes up the following form:

$$\min_{\{\boldsymbol{u}_\tau\}_{\tau=t,\dots,t+h-1}} \sum_{\tau=t}^{t+h-1} g_\tau\left(\boldsymbol{x}_\tau, \boldsymbol{u}_\tau, \boldsymbol{d}_{\tau+1}\right) + g_{t+h}\left(\boldsymbol{x}_{t+h}\right) \quad \text{(1a)}$$

subject to:

$$0 < \boldsymbol{u}_\tau < \boldsymbol{u}_{max} \qquad \tau = t,\dots,t+h-1 \qquad \text{(1b)}$$

$$x_{\tau+1} = f_\tau\left(x_\tau, u_\tau, d_{\tau+1}\right) \qquad \tau = t,\dots,t+h-1 \qquad \text{(1c)}$$

where: $\boldsymbol{u}_t, \dots, \boldsymbol{u}_{t+h-1}$, is the sequence of decisions to be taken over the prediction horizon, i.e. the inflow/outflow release volumes for each reservoir and each time interval, that must respect the physical hard-constraint of the channels capacity $\boldsymbol{u}_{max}$ (reported in Table 1); *h* is the length of the prediction horizon; the vector $\boldsymbol{x}_\tau$ is the system state, which includes the 4 reservoir storages plus 51 state variables of the hydraulic model of the river network; g_τ is a *step-cost function* that expresses the cost associated to the transition from time τ to time τ+1. In our case study, it encompasses two different objectives: floods control and water supply in low-flows periods. Its definition is further detailed below, here we just point out that, as g_τ is computed from the simulated river flows, it is a function of the system state ($\boldsymbol{x}_\tau$), the control decisions $(\boldsymbol{u}_\tau)$ and the exogenous system input $(\boldsymbol{d}_{\tau+1})$, i.e. in our case the meteorological forcing of the hydrological model, as given by the deterministic weather forecast available at time t. Finally, $g_{t+h}\left(\boldsymbol{x}_{t+h}\right)$ is a penalty-cost that expresses the cost paid for reaching a more or less desirable state at the end of the prediction horizon. Eq. (1c) represents the state-space model that, in our study, takes the form of the complex hydrological-hydraulic model described in the previous section. The recursive application of Eq. (1c) is initialized by the value $\boldsymbol{x}_t$ of the state at current time t, which is another input data of the problem together with the meteorological forcing forecasts.

Since deterministic MPC does not take into account forecast uncertainty, its performance can be limited by an excess of confidence in the anticipated system response. To overcome the problem and reduce the sensitivity of the control strategy to wrong forecasts, Ensemble forecasts (EF) can be used in place of deterministic ones. Raso et al. (2014) proposed an extension of MPC that can deal with EFs, called Tree-Based (TB) MPC. In TB-MPC, the ensemble is transformed into a tree where ensemble members that are sufficiently similar are bundled together into one trajectory (branch) up to the point when some of them start to significantly diverge from the others, and the trajectory is split into different branches. The tree structure is then used in the TB-MPC algorithm, which optimizes a "control tree" that defines a distinct control sequence for each branch. Control sequences are constrained to be the same up to the moment when two ensemble members branch out, which translates the *non-anticipativity condition* (see Eq. 5 in Raso et al., 2014) stating that control actions should not depend on the outcome of stochastic variables that have not been extracted yet (Birge and Louveaux, 1997). The tree structure generation can be done by using the methodology proposed by Raso et al. (2013). To reduce the computing time, the tree is generated after reducing the EFs through the scenario reduction algorithm by Growe-Kuska et al. (2003). This method produces a reduced ensemble of prescribed cardinality by deleting some ensemble members according to a minimization process based on a mass transportation metric. The choice of the reduced ensemble cardinality is a compromise between reduction in computing time and loss of accuracy and it is case dependent. In our case, following the suggestions given in Stive (2011), we fixed the cardinality of the reduced ensemble to 6. To represent the tree structure and implement the non-anticipative condition in the TB-MPC formulation, we used a *scenario tree nodal partition matrix M* (Dupacova et al., 2003). Each element of this matrix, say element (i, j), is the label number of the branch in the tree to which the ensemble member *j* belongs at time-step *i*. The maximum value in *M* corresponds to the number of branches in the tree, and thus of distinct control actions along the tree. Having introduced *M*, the objective function for the TB-MPC problem is defined as:

$$\min_{U_{M_t}} \sum_{z=1}^{n} p(z) \left[\sum_{\tau=t}^{t+h-1} g_\tau \left(\boldsymbol{x}_{\tau,z}, \boldsymbol{u}_{M_t(\tau,z)}, \boldsymbol{d}_{\tau+1,z} \right) + g_{t+h} \left(\boldsymbol{x}_{t+h,z} \right) \right] \qquad (2a)$$

subject to:

$$0 < \boldsymbol{u}_{M_t(\tau,z)} < \boldsymbol{u}_{max} \qquad \forall\, z \text{ and } \tau = t, \ldots, t+h-1 \qquad (2b)$$

$$x_{\tau+1,z} = f_\tau \left(x_{\tau,z}, u_{M_t(\tau,z)}, d_{\tau+1,z} \right) \qquad \forall\, z \text{ and } \tau = t, \ldots, t+h-1 \qquad (2c)$$

where: U_{M_t} is a matrix that includes all the control actions taken over the prediction horizon along the different branches of the tree, and whose structure is defined by the nodal partition matrix M_t, where the subscript indicates that *M* is built from the ensemble at time t; $p(z)$ is the probability of the *z-th* ensemble member; $\boldsymbol{d}_{t+1,z}$ is the disturbance forecast according to the *z-th* ensemble member; $\boldsymbol{x}_{\tau,z}$ is the *state vector* at time τ under the disturbances trajectory produced by the *z-th* ensemble member, given the initial state; $\boldsymbol{u}_{M_t(\tau,z)}$ is the control action at time τ along the branch associated to the *z-th* ensemble member, whose position in matrix U_{M_t} is given by $M_t(\tau, z)$. Before a branching point, the nodal partition matrix returns the same position and thus the same control value for all ensemble members on the same branch, respecting the non-anticipativity condition. After the branching point, it returns different addresses for members in different branches and thus allows for different control values.

The length of the prediction horizon h was fixed equal to 9 days in both the MPC and TB-MPC case, because this is the maximum lead-time of available forecasts, and sensitivity analysis tests showed that the performance steadily improves with the length of the prediction horizon. These results are further described in Ficchì (2013) and they are in line with previous studies (e.g. Pianosi and Ravazzani, 2010).

Since our optimization problems (Eq. 1 or 2) cannot be solved analytically, they are solved by the direct search Nelder-Mead algorithm (Nelder and Mead, 1965), a derivative-free method for nonlinear optimization. The optimizer uses simulation results of the hydrological-hydraulic model for the re-iterated evaluation of the objective function. To improve the convergence and reduce the computing time, we found it convenient to reduce the number of decision variables by enlarging the duration of application of each decision. Since the decision for the first daily time interval in the prediction horizon is the only one that is actually applied, we forced a daily duration for this first decision. For the subsequent time intervals, instead, we allow for a time-varying duration, with a finer temporal resolution at the beginning of the prediction horizon in case of high-flows conditions, and a coarse resolution in low-flows conditions, when inflows have lower variance. Specifically, in high-flows conditions decision values are changed at time steps 1, 2, 3 and 5 in the prediction horizon, while in normal or low-flows conditions they are changed at time steps 1 and 2 only. The resulting search space of the optimization problem is thus larger in case of high-flows. For deterministic MPC, the total number of decision variables is 32 in high-flows conditions (8 variables at 4 time steps) and 16 otherwise (8 variables at 2 time steps). In TB-MPC, the number of decisions depends on the tree-structure, and specifically on the number of distinct branches at the last decision time-step (i.e. $\max(M(\tau=5,z)$ in high-flows conditions, and $\max(M(\tau=2,z)$ otherwise). Such a number varies between 4 and 18 in case of high-flows, for a total of 8x4=32 and 8x18=144 decision variables, and between 2 and 6, i.e. 16 and 48 variables, otherwise. When a branching point does not fall on the time-step when the decision can be changed, it is shifted to the following decision-step. This choice is analogous to the one in Raso et al. (2013) and is motivated by the fact that observations available at higher frequency than the decision frequency cannot be used until a new control is chosen.

Step-costs

The step-cost function g_t (Eqs. (1a) and (2a)) expresses all the "costs" that the operation of the reservoirs may produce on day t. In our case study, this includes four components, which reflect the operation targets and constraints: the fact that river flows at the downstream monitoring stations do or do not exceed one of the high or low flow thresholds; the fact that reservoir levels do or do not exceed the minimum or maximum allowed levels; and finally the fact that the minimum environmental flows and the maximum reference flows are or are not guaranteed. The step-cost function takes up the following form:

$$g_t^{tot} = \sum_{j=1}^{N_s}(g_t^{j,hf} + g_t^{j,lf}) + \sum_{r=1}^{N_r} g_t^{r,V} + \sum_{i=1}^{N_i} g_t^{i,In} + \sum_{o=1}^{N_o} g_t^{o,Out} \quad (3)$$

where N_s is the number of downstream stations and the $g^{j,hf}$ and $g^{j,lf}$ functions measure the violation of high and low flow thresholds; N_r is the number of reservoirs (four) and $g^{r,V}$ measures the violation of minimum and maximum reservoir limits; N_i is the number of inlet channels and $g^{i,In}$ measures the violation of minimum environmental flow constraints; N_o is the number of outlet channels and $g^{o,Out}$ measures the violation of maximum reference flow constraints. The components of the step-cost function are further described below.

Step-costs for high and low flows

For high-flows, a cost is encountered when the river flow at a downstream station exceeds the flood warning thresholds. At each station *j* there are three flooding thresholds to be respected with increasing priority (Table 2). These thresholds are based on the French national flood forecast center (SCHAPI, www.vigicrues.gouv.fr) classification: the first threshold (vigilance) corresponds to the bankfull discharge where no flood occurs yet but special vigilance may be required; the second threshold (alert) corresponds to frequently flooded area with potentially significant impacts on community life and the safety of goods and people; and the third threshold (crisis) corresponds to an exceptionally large flooded area, and a direct and widespread threat to safety of people and goods. The step-cost function is set to zero until the flow exceeds the vigilance threshold and almost approaches the second flooding threshold $\overline{q^j_{hf,a}}$, precisely when it reaches the value:

$$\overline{q^{j}_{hf\,1}} = \overline{q^j_{hf,\mathrm{v}}} + 0.9\left(\overline{q^j_{hf,a}} - \overline{q^j_{hf,\mathrm{v}}}\right). \qquad (4)$$

From the above value onward, the step-cost function increases piece-wise linearly with the river flow, i.e.:

$$g_t^{\,j,hf} = \begin{cases} 0 & \text{if } q_t^j < \overline{q^j_{hf1}} \\ \alpha_{hf,j}\left(q_t^j - \overline{q^j_{hf1}}\right) & \text{if } \overline{q^j_{hf1}} \le q_t^j < \overline{q^j_{hf,a}} \\ \beta_{hf,j}\left(q_t^j - \overline{q^j_{hf,a}}\right) + \alpha_{hf,j}\left(\overline{q^j_{hf,a}} - \overline{q^j_{hf1}}\right) & \text{if } \overline{q^j_{hf,a}} \le q_t^j < \overline{q^j_{hf,\mathrm{c}}} \\ \gamma_{hf,j}\left(q_t^j - \overline{q^j_{hf,c}}\right) + \beta_{hf,j}\left(\overline{q^j_{hf,c}} - \overline{q^j_{hf,a}}\right) + \alpha_{hf,j}\left(\overline{q^j_{hf,a}} - \overline{q^j_{hf1}}\right) & \text{if } q_t^j \ge \overline{q^j_{hf,c}} \end{cases} \qquad (5)$$

where q_t^j is the river flow at time *t* and station *j*; $\overline{q^{j}_{hf\,1}}$ is the flow value defined by Eq. (4); $\overline{q^j_{hf,a}}$ and $\overline{q^j_{hf,c}}$ are the alert and crisis high-flow thresholds; and $\alpha_{hf,j} < \beta_{hf,j} < \gamma_{hf,j}$ are the slopes of the piecewise linear function.

For low-flows, a cost is encountered when the river flow goes below the regulatory thresholds (Table 2). Again, we use a piecewise linear cost function with a changing slope in correspondence to the different thresholds, i.e.:

$$g_t^{j,lf} = \begin{cases} 0 & \text{if } q_t^j > \overline{q_{lf,al}^j} \\ \alpha_{lf,j}\left(\overline{q_{lf,al}^j} - q_t^j\right) & \text{if } \overline{q_{lf,ra}^j} < q_t^j \le \overline{q_{lf,al}^j} \\ \beta_{lf,j}\left(\overline{q_{lf,ra}^j} - q_t^j\right) + \alpha_{lf,j}\left(\overline{q_{lf,al}^j} - \overline{q_{lf,ra}^j}\right) & \text{if } \overline{q_{lf,cr}^j} < q_t^j \le \overline{q_{lf,ra}^j} \\ \gamma_{lf,j}\left(\overline{q_{lf,cr}^j} - q_t^j\right) + \beta_{lf,j}\left(\overline{q_{lf,ra}^j} - \overline{q_{lf,cr}^j}\right) + \alpha_{lf,j}\left(\overline{q_{lf,al}^j} - \overline{q_{lf,ra}^j}\right) & \text{if } q_t^j \le \overline{q_{lf,cr}^j} \end{cases} \quad (6)$$

where q_t^j is the river flow at time t and station j; $\overline{q_{lf,al}^j}$, $\overline{q_{lf,ra}^j}$, and $\overline{q_{lf,cr}^j}$ are the alert, reinforced alert and crisis thresholds (corresponding to a restriction of water uses of 30%, 50% and 100%, respectively); and $\alpha_{lf,j} < \beta_{lf,j} < \gamma_{lf,j}$ are the slopes of the piecewise linear cost.

The choice of the slope values (α, β, γ) is subjective and should translate the preference system of the reservoirs operators. In this study, the value for these parameters was identified in such a way to find a reasonable balance between step-costs and the penalty-cost on the final storages, as further detailed below in the section on “Weighting step-costs and penalty functions”.

Step-costs for reservoirs limits and downstream environmental and reference flows

For each reservoir r we defined the *soft-constraint* cost $g_t^{r,V}\left(V_t\right)$, associated to exceeding the volumes thresholds, as:

$$g_t^{r,V}\left(V_t\right)=\begin{cases}0 & \text{if } (V_{\min}^r+fs)<V_t^r<(V_{\max}^r-fs)\\ w_{sc,V}\left(V_t^r-V_{\min}^r-fs\right)^2 & \text{if } V_t^r\le\left(V_{\min}^r+fs\right)\\ w_{sc,V}\left(V_{\max}^r+fs-V_t^r\right)^2 & \text{if } V_t^r\ge\left(V_{\max}^r-fs\right)\end{cases}\tag{7}$$

where: V_t^r , V_{min}^r and V_{max}^r are respectively the current, minimum and maximum volumes of the reservoir r; fs is a security factor (e.g. we defined it as one thousandth of the range [V_{min}^r, V_{max}^r]); $w_{sc,V}$ is the weight, that we defined as a very high number (e.g. 10^{15}) to get a soft-constraint cost $g_t^{r,V}\left(V_t\right)$ higher than all the other cost-components even for volumes at the limits ($V_t = V_{min}$ or $V_t = V_{max}$), as we want these limits to be respected in priority.

The reserved flow (Table 1) is a legal constraint that defines the minimum flow to be left in the river downstream from an inlet channel. For each downstream river station (say the *i*-th), we defined the *soft-constraint* cost $g_t^{i,In}\left(Q_t^i\right)$ as:

$$g_t^{i,In}\left(Q_t^i\right)=\begin{cases}0 & \text{if } Q_t^i>Q_{res}^i\, fs\\ w_{sc,Q_{res}}\left(Q_t^i-Q_{res}^i\, fs\right)^2 & \text{if } Q_t^i\le Q_{res}^i\, fs \text{ and } \mathrm{Q}_t^i>0\end{cases}\tag{8}$$

where Q_t^i is the current river flow at time t and station i, Q_{res}^i the reserved flow at the station i and fs a security factor; the weight $w_{sc,Q_{res}}$ is adjusted to get a soft-constraint cost $g_t^{i,In}\left(Q_t^i\right)$ higher than the other cost-components (except for $g_t^{r,V}\left(V_t\right)$).

The reference flow (Table 1) is a constraint for the reservoir operation limiting the reservoirs discharge in order to avoid floods immediately downstream from the reservoirs outlet channels. For each downstream station (say the *o*-th), we defined the step-cost $g_t^{o,Out}\left(Q_t^o\right)$ as:

$$g_t^{o,Out}\left(Q_t^o\right)=\begin{cases}0 & \text{if } Q_t^o < Q_{ref}^o\, fs \\ w_{Q_{ref}}\left(Q_t^o - Q_{ref}^o\, fs\right)^2 & \text{if } Q_t^o \geq Q_{ref}^o\, fs \text{ and } u_t^o > 0\end{cases} \tag{9}$$

where Q_t^o is the current river flow at time *t* and station *o*; Q_{ref}^o the reference flow at the station *o;* and $w_{Q_{ref}}$ is a weight lower than the other cost-components weights.

Penalty-cost on the final state

The penalty-cost g_h over the final state is introduced with the aim of including the long-term management targets into the formulation of the objective function of Eqs. (1a) and (2a) which would otherwise consider only the costs encountered during the prediction horizon. In our case study application, the penalty-cost is a function of the reservoir volumes at the end of the prediction horizon and it increases with the deviations from the most desirable volumes for that time instant. Such "desirable volumes" are linked to those defined by the reservoirs rule-curves, so that the penalty function is a means for ensuring consideration of the water supply objective even using a short-term prediction horizon. Specifically, g_h takes up the following form:

$$g_h = \sum_{i=1}^{4} w_i(\mathrm{V}_h^i)\ (\mathrm{V}_h^i - \mathrm{V}_{RC,h}^i)^2 + \theta_i(\mathrm{V}_h^i) \tag{10}$$

where V_h^i is the storage of the *i*-th reservoir at time *h*; $V_{RC\ h}^i$ is the target volume according to the rule-curve of the *i*-th reservoir for time *h*; w_i and θ_i are weight coefficients that can take up one out of 7 values, depending on the value of the reservoir storage V_h^i. Specifically, for each reservoir we define 2 thresholds above the rule-curve and 3 below it, which determine the switch to an increased weight value. These volume thresholds are defined as follows:

(i) The three thresholds below the target $V^{i}_{RC\ h}$ are computed by integrating the differences in flow between the low-flows thresholds (alert, reinforced alert, and crisis) at the most downstream station in Paris all over the drawdown season. The approach is similar to the one proposed by Bader (1992), implicitly assuming that the RC target is constructed to ensure that the first low-flow threshold (vigilance) at Paris can be respected throughout the drawdown season.

(ii) The two thresholds above the target $V^{i}_{RC\ h}$ are defined by a manual tuning process, to ensure a fixed storage capacity to avoid exceeding the higher flood thresholds (alert and crisis).

The seven weight values w_i for each storage range above/below the RC target are defined jointly with the weight values of the step-costs for high and low flows, according to a procedure described in the next paragraph.

Weighting step-costs and penalty functions

When an exceptional event is forecasted over the prediction horizon, the effect of the step-costs for high and low flows (Eqs. (5) and (6)) is to make the system diverge from the RCs, while the effect of the penalty function (Eq. (10)) is to force it to converge back to the RCs. The relative weights given to these components thus define the balance between the conflicting objectives of exploiting the system capacity to tackle floods and droughts in the short-term, or saving this capacity for later. The slope coefficients $\alpha_{hf,j}$, $\beta_{hf,j}$, $\gamma_{hf,j}$ and $\alpha_{lf,j}$, $\beta_{lf,j}$, $\gamma_{lf,j}$ of Eqs. (5) and (6) and the weight values w_i in Eq. (10) regulate the relative importance of short and long term objectives. In this study, such coefficients were computed analytically by solving a balance equation where the total penalty-cost for having all storages at a given volume threshold is set equal to the sum of the step-costs for having flows in all stations at the corresponding flow threshold (for *h* days in case of low-flows, and the average duration of that flow threshold event for high-flows). By doing so, the future system capacity to tackle an extreme event that may occur beyond the prediction horizon is not compromised by the need of tackling an event of the same severity within the prediction horizon.

Results

We report here the results of the comparison between the "no-forecast" management strategy, essentially based on rule-curves as in the actual system operation, and the management strategies that use different forecast types, by means of the MPC and TB-MPC optimization algorithms. Simulation results are presented in two steps: first we compare the "no-forecast" strategy with the use of perfect forecasts in MPC; then, we compare the use of deterministic and ensemble forecasts in MPC and TB-MPC. Because of limited data availability, we use a different simulation period in the two cases (see further discussion below).

"No-forecast" operation vs MPC with perfect forecasts

First we compare the "no forecast" operation based on rule-curves and MPC with perfect forecasts. Fig. 3(a) reports the temporal average of the step-costs for high and low flows (Eqs. (5) and (6)) aggregated for all the stations over a simulation horizon of 15 years (1973-1988). These values are normalized with respect to the average-costs that would have been encountered over the same horizon in the hypothetical scenario where reservoirs were not in operation. A value of 0 thus means that the reservoirs operation does not induce any change with respect to "unregulated conditions" while a value of 1 means that it can completely eliminate all costs. Fig. 3(a) shows that while Rule-Curves (RCs) can guarantee a reduction in average costs of about 90% for floods and nearly 80% for low-flows, the implementation of the MPC strategy with Perfect Forecasts (MPC-PF) would further reduce costs to the 98% for floods and slightly more than 80% for low-flows. Notice that although the most significant improvement in the system performance obviously comes from the construction of the reservoirs, regardless of their operation, the further improvement ensured by MPC would come at relatively low cost as compared to infrastructural interventions.

Figs. 3(b,c,d,e,f) report some complimentary statistics (frequency, duration, etc.) of the flow threshold violations under the two different management strategies. These statistics show that MPC with Perfect Forecasts could almost completely eliminate flood risk. As for low-flow conditions, MPC-PF would have a more limited impact (and no effects on statistics in Figs. 3(d,e,f)), possibly because low-flow events should be anticipated over a longer time span (say weeks or months) than the prediction horizon used here (9 days).

Fig. 4(a) provides a representative example of the simulated flow trajectory in a downstream river station (Paris) during the most severe flood event in the available historical horizon (January 1982). During this event, under the “no-reservoirs” scenario the river flows would have been above the third high-flow threshold (crisis) at one downstream station and above the second threshold (alert) at almost all others. With reservoirs operated according to the rule-curves, the crisis thresholds are not exceeded but the alert thresholds are, for 39 days between December 1981 and February 1982. MPC-PF instead can maintain downstream river flows below the alert thresholds almost all the time, exceeding them only for 7 days. Fig. 4(b) reports the temporal evolution of the four reservoirs volumes over the same flood event, showing that, from about January, 4th when the upcoming flood event appears in the prediction horizon, all the four reservoirs are being increasingly filled in and thus contribute to reducing high-flows downstream costs by storing water to an extent proportionally to their actual capacity (see reservoirs capacity in Table 1). Fig. 4 provides a representative example of the proactive and centralized behavior of the MPC management. However, these results are an upper bound of the improvement that could be provided by MPC in the hypothetical case that weather forecasts were perfect. The performances that could be actually obtained by feeding MPC with real forecasts are discussed in the next subsection.

MPC with real deterministic forecasts vs TB-MPC with ensemble forecasts

Here we present and compare the simulation results of the MPC strategy fed by real, deterministic forecasts and the TB-MPC strategy fed by Ensemble Forecasts. To simulate these strategies over a historical horizon, hindcast time-series from the ECMWF model are used. These are available from 11/3/2005 to 01/10/2008. Since there are no critical flood events over this time horizon, we lowered the high-flows thresholds to artificially increase the pressure over the system and generate some "critical" events where the different management strategies can be compared. Because we use lower thresholds, the simulation of the no-forecast operation, which implicitly takes into account the actual thresholds in the definition of the RCs, is not sensible. This is not a main limitation given that the focus here is on comparing the use of deterministic forecasts (by MPC) and ensemble forecasts (by TB-MPC). As a reference we will rather use the performances obtained by using perfect forecast, so that the comparison will address the following questions: (i) what is the loss in system performances due to forecast uncertainty? (ii) Does the system operation improve if we explicitly take into account forecast uncertainty, as represented by EF? As a performance indicator, we use the temporal average of the high-flows step-costs (Eq. (5), aggregated at all the stations) normalized with respect to the average step-costs that would have been encountered with perfect forecasts. The lower this value, the closer the reservoirs operation is to the "ideal" scenario where forecasts are perfect. The indicator can thus be regarded as a measure of the loss in performance due to forecast uncertainty. Fig. 5(a) reports the value of such loss indicator (in %) over the (artificial) flood event in 2007 under the MPC and TB-

MPC operation (i.e. with real deterministic and ensemble forecasts), showing that the use of EF greatly reduces the performance loss due to forecast uncertainty. In fact, during this event, river flows produced by TB-MPC are consistently lower than with MPC, and closer to the “ideal” ones produced with perfect forecasts (Fig. 6). To complement the analysis, Figs. 5(b-f) provide some other statistics on threshold violations (analogously to Fig. 3). They confirm that taking into account forecasts uncertainty via EF improves the system operation by all aspects. These benefits are achieved at the cost of an increased computational burden: the computational time of TB-MPC is about 7 times greater than that of MPC. However, in both cases the average computing time is compatible with the needs of real-world decision-makers: on a standard desktop machine (Intel® core™ i5-2410M, 2.9 GHz), for each day of simulation, MPC delivers a solution to the deterministic problem of Eq. (1) in about 82 seconds, TB-MPC delivers a solution of the uncertain problem of Eq. (2) in about 567 seconds, i.e. less than 10 minutes.

Discussion and conclusions

We have presented the implementation and evaluation of a centralized real-time optimization system that uses deterministic and ensemble weather forecasts to improve the management of a multi-reservoirs system in the Seine River basin in France. To anticipate the system response to input forecasts, the optimization system is coupled with a semi-distributed hydrological model of the watershed, a simplified hydraulic model of the river network and the four reservoir models. Optimization seeks to minimize the costs associated to high and low flows, and a penalty-cost based on the reservoir storages at the end of the prediction horizon, which takes into account the long-term management objectives defined by the reservoirs rule-curves.

We first consider the idealized case when the real-time optimization system is fed by perfect forecasts (PF) and show that it clearly outperforms the management strategy that does not use forecasts and simply follows the rule-curves, in particular in high-flows conditions. Over the 15-year simulation horizon, the real-time system can always maintain downstream river flows below the crisis thresholds (exceptionally flooded areas) and can reduce the number of days in which the alert threshold (frequently flooded areas) is exceeded by about 80%. These results suggest that, if efficiently managed, the current infrastructure could almost completely eliminate flood risk in the ideal situation where weather forecasts were perfect.

In order to assess the performance loss due to forecasts uncertainty, we simulated the real-time optimization system with actual weather forecasts produced by the ECMWF model. Results show that while the use of actual deterministic forecasts obviously reduces the system performances for flood control, the explicit consideration of forecast uncertainty by the use of a forecasts ensemble can almost fill in such a performance loss, and it provides results almost as good as in the perfect forecasts case. This conclusion is in line with previous results reported for instance in Roulin (2007), Pianosi and Ravazzani (2010) and Raso et al. (2014) .

The work here presented is affected by some limitations that could be addressed by future research. First, since hindcast weather forecasts were available only over a short time horizon when no significant flood events occurred, the comparison between the use of deterministic and ensemble forecasts was performed by considering flow thresholds that are actually lower than real ones. Although the comparison remains perfectly fair and valid as a proof-of-concept, it would be interesting to further compare the two management approaches under a real critical high flow event. Further research will also aim at differentiating the simulation model used in closed-loop simulation from the internal model used in MPC optimization, in order to investigate the impact of the hydrological-hydraulic model uncertainty on the MPC performances. The operation model implementing MPC and TB-MPC should also be improved, testing different direct search methods, possibly more efficient than Nelder-Mead. In fact, in our experiments optimization runs were sometimes terminated before reaching convergence. Therefore, results here presented may underestimate the improvement that the use of weather forecasts produces with respect to the "no forecast" management based on Rule Curves. Finally, the centralized, real-time optimization system will be tested under projected climate change scenarios. In fact, despite the limitations above discussed, our analysis seems to indicate that a more efficient reservoir operation system, using weather forecasts and explicitly considering forecast uncertainty, is likely to significantly reduce flood risk under the historical hydrological conditions. The next step will be to assess whether this would hold true also in a possible future scenario where the frequency and intensity of extreme events were increased. Although assessing the probability of such a future scenario is beyond our current knowledge because of the deep uncertainty that affects climate change impacts studies (Wilby and Dessai, 2010), the implementation of the real-time optimization system here presented represents a "no-regret" strategy that, by improving the system efficiency, could yield benefits regardless of climate change (assuming that weather forecasting skill will not decrease), and mitigate its impacts whenever occurring.

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Fig. 1 Map of the Seine River basin at Paris with the main river network (1810 km), the four reservoirs and their inlets and outlets, the 25 sub-basins, and the gauging and monitoring stations.

Fig. 2 Information fluxes of the two management strategies compared in this work. Left: the uncoordinated, feedback operation that is currently being employed and is based on Rule-Curves (RCs) (“no-forecast operation”). Right: the centralized feed-forward MPC operation using weather forecasts.

Fig. 3 Performance of the “no-forecast” operation based on Rule-Curves (RCs) and of the MPC operation fed by Perfect Forecasts (MPC PF) over the 15-year simulation horizon (from 01/08/1973 to 01/11/1988), averaged over monitoring stations. (a) Improvement in the average step-costs with respect to the “no-reservoirs” scenario. (b) Total number of days with violation of the alert thresholds. (c) Mean duration of violation events. (d) Maximum duration of violation events. (e) Maximum flow exceedance with respect to the alert thresholds. (f) Number of monitoring stations with at least one violation event over the simulation horizon.

Fig. 4 (a) Simulated flow of the Seine River at Paris station during the 1982 flood event under the “no-forecast” management based on Rule-Curves (RC, grey line), and under MPC with perfect forecasts (MPC-PF, black). The two horizontal dashed and thick lines are the high-flows thresholds ($\overline{q^j_{hf,a}}$ and $\overline{q^j_{hf,c}}$), while the thin dashed line is the level ($\overline{q^j_{hf1}}$) where the high-flows step-costs start to increase. (b) Simulated volumes of the four reservoirs during the same event under MPC operation fed by Perfect Forecasts.

Fig. 5 Performance of the MPC operation with Perfect Forecasts (PF), Deterministic Forecasts (DF) and Ensemble Forecasts (EF) over a flood event in 2007, averaged over monitoring stations. (a) Loss in performance due to forecast uncertainty (with respect to perfect forecasts). (b) Total number of days with violation of the (alert) thresholds. (c) Mean duration of violation events. (d) Maximum duration of violation events. (e) Maximum flow exceedance with respect to the alert thresholds. (f) Number of monitoring stations with at least one violation event over the simulation horizon.

Fig. 6 Simulated flows of the Seine River at Paris station under MPC with perfect forecasts (PF, thin black line), MPC with deterministic forecasts (DF, gray line with triangles) and TB-MPC with ensemble forecasts (EF, dashed line with circles). The two horizontal dashed lines are the high-flows thresholds ($\overline{q^{j}_{hf,a}}$ and $\overline{q^{j}_{hf,c}}$; values are lower than in Table 2, see text for explanation), the dotted line is the level ($\overline{q^{j}_{hf1}}$) where step-costs for high-flow become non-zero.

Table 1. Reservoirs, channels capacity, and constraints on river flow downstream from reservoirs inlets and outlets.

Reservoir	**Maximum exceptional capacity [Mm^3]**	**Maximum outlet flow [m^3/s]**	**Maximum inlet flow [m^3/s]**	**Reserved flow [m^3/s]**	**Reference flow [m^3/s]**
Aube	183.5	35	135	From 2 to 4 depending on the month	130
Marne	364.5	50	Main inlet channel: 375	From 2 to 3 depending on the month	From 40 to 120 depending on the month
			Secondary inlet channel: 33	From 5 to 8 depending on the month	
Pannecière (Valley-dammed)	82.5	16	-	0.6	From 11.4 to 14 depending on the month
Seine	219.5	35	200	From 3 to 6 depending on the month	From 55 to 120 depending on the month

Table 2. Monitoring stations downstream from the reservoirs (A=Aube, M=Marne, P=Pannecière, S=Seine) and thresholds for low-flows (vigilance $\overline{q_{lf,\mathrm{vig}}}$, alert $\overline{q_{lf,al}}$, reinforced alert $\overline{q_{lf,ra}}$ and crisis $\overline{q_{lf,cr}}$) and high-flows (vigilance $\overline{q_{hf,v}}$, alert $\overline{q_{hf,a}}$ and crisis $\overline{q_{hf,c}}$).

Monitoring stations			**Low-flow thresholds (m^3/s)**				**High-flow thresholds (m^3/s)**		
Gauging station	**River**	**Upstream reservoirs**	**Vigilance (sensitivity to pollution)**	**Alert (water use reduction: 30%)**	**Reinforced alert (water use reduction: 50%)**	**Crisis (water use reduction: 100%)**	**Vigilance (bankfull discharge)**	**Alert (frequently flooded areas)**	**Crisis (exceptionally flooded areas)**
Arcis-sur-Aube	Aube	A	6.3	5.0	4.0	3.5	110	260	400
Méry-sur-Seine	Seine	S	7.3	5.0	4.0	3.5	140	170	400
Nogent-sur-Seine	Seine	A+S	25.0	20.0	17.0	16.0	180	280	420
Gurgy	Yonne	P	14.0	12.5	11.0	9.2	220	340	400
Courlon-sur-Yonne	Yonne	P	23.0	16.0	13.0	11.0	550	700	900
Alfortville	Seine	A+S+P	64.0	48.0	41.0	36.0	850	1 200	1 400
Châlons-sur-Marne	Marne	M	12.0	11.0	9.0	8.0	330	520	700
Noisiel	Marne	M	32.0	23.0	20.0	17.0	350	500	650
Paris	Seine	A+S+P+M	81.0	60.0	51.0	45.0	950	1 600	2 000

Table 3. Ensemble Forecasts mean, spread (i.e. standard deviation) and Root Mean Square Error (RMSE), at lead-time from 1- to 9-days ahead.

Lead-time [d]	1	2	3	4	5	6	7	8	9
Mean [mm]	1.68	2.42	2.36	2.34	2.40	2.46	2.49	2.48	2.43
Spread [mm]	0.97	1.62	2.14	2.52	2.82	3.13	3.34	3.50	3.56
RMSE [mm]	3.32	2.73	3.64	4.07	4.00	3.91	3.87	3.79	3.66