Hydrol. Earth Syst. Sci., 16, 189–199, 2012
www.hydrol-earth-syst-sci.net/16/189/2012/
doi:10.5194/hess-16-189-2012


Hydrology and Earth System Sciences

# Assessing water reservoirs management and development in Northern Vietnam

**A. Castelletti[1], F. Pianosi[1], X. Quach[1,2], and R. Soncini-Sessa[1]**

[1]Dipartimento di Elettronica e Informazione, Politecnico di Milano, Milan, Italy
[2]Institute of Water Resources Planning, 162A, Tran Quang Khai, Hanoi, Vietnam

*Correspondence to:* F. Pianosi (pianosi@elet.polimi.it)

Received: 14 July 2011 – Published in Hydrol. Earth Syst. Sci. Discuss.: 20 July 2011
Revised: 27 December 2011 – Accepted: 6 January 2012 – Published: 23 January 2012

**Abstract.** In many developing countries water is a key renewable resource to complement carbon-emitting energy production and support food security in the face of demand pressure from fast-growing industrial production and urbanization. To cope with undergoing changes, water resources development and management have to be reconsidered by enlarging their scope across sectors and adopting effective tools to analyze current and projected infrastructure potential and operation strategies. In this paper we use multi-objective deterministic and stochastic optimization to assess the current reservoir operation and planned capacity expansion in the Red River Basin (Northern Vietnam), and to evaluate the potential improvement by the adoption of a more sophisticated information system. To reach this goal we analyze the historical operation of the major controllable infrastructure in the basin, the HoaBinh reservoir on the Da River, explore re-operation options corresponding to different tradeoffs among the three main objectives (hydropower production, flood control and water supply), using multi-objective optimization techniques, namely Multi-Objective Genetic Algorithm. Finally, we assess the structural system potential and the need for capacity expansion by application of Deterministic Dynamic Programming. Results show that the current operation can only be relatively improved by advanced optimization techniques, while investment should be put into enlarging the system storage capacity and exploiting additional information to inform the operation.

## 1 Introduction

Starting in the late Eighties, Vietnam has undertaken a comprehensive reform (Doi Moi) of liberalization of economic production and exchange, which has been the key driver of its explosive economic and demographic development in the last two decades (Toan et al., 2011). The rapid growth resulted in an increased energy demand, which has been growing at an annual rate of nearly 15 % in the last ten years; but also boosted internal migration from rural areas to the main cities, which are sprawling uncontrolled (Hoang et al., 2010). Water resources play a central role in this development: hydropower is the primary renewable energy resource in the country (33 % of the total electric power production) and, despite the considerably increasing importance of the industrial and service sectors, agriculture (76 % of whose product comes from irrigated land) is still an important economic drive (Nguyen et al., 2002) – which contributes for 18 % to the GDP, but employes 70 % of the population – and a primary source to ensure food security in the face of demand pressure. Unfortunately, water is also responsible for most of the worst natural disasters that occurred in the country in recent years (Hansson and Ekenberg, 2002). Severe floods are plaguing Hanoi every year during the heavy rain monsoon season with increasing damage in the unusually overdeveloped river urban area.

To cope with this heterogeneous and fast-evolving context, water resources development and management needs to be reconsidered to improve resilience of economy, society

Published by Copernicus Publications on behalf of the European Geosciences Union.

and environment in the entire Vietnam. Increased water storage at the river basin level is certainly a major component of vulnerability reduction strategies, however the optimal re-operation of the available storing capacity is an economically interesting and potentially effective alternative, or simply complementary option, to infrastructure development.

In this paper we use multi-objective deterministic and stochastic optimization to assess the current management of the Red River Basin, the second largest basin of Vietnam, and the room for improvement accounting for the multiple and conflicting objectives of hydropower production, flood control and water supply to irrigated agriculture. We focus on the major controllable infrastructure in the basin, the HoaBinh reservoir on the Da River, that produces about 15 % of the annual national electricity. We analyze the historical dam operation and explore re-operation options corresponding to different tradeoffs among the three objectives, using multi-objective optimization techniques. Finally, we assess the structural system potential and the need for capacity expansion by application of deterministic optimization.

In the literature, we found only two works on the operation of the HoaBinh reservoir. Ngo et al. (2008) use traditional scenarios analysis to comparatively assess three alternative operating policies on flood control and hydropower production focusing on the flood season only. Built on these results, Ngo et al. (2007) explore the reservoir re-operation by parameterization and subsequent optimization of the operating rules through the Shuffled Complex Evolution algorithm. In this paper we take a step forward by: (i) enlarging the trade-off analysis to the water supply sector; (ii) enlarging the optimization horizon to the entire year thus allowing for inter seasonal water transfer; (iii) exploiting more data availability to introduce a clear distinction between the dataset used for optimization and the one used for validation of the optimized policies, which allows for a fair and statistically sound comparison with the historical operation. From the methodological standpoint, this study constitutes an example of how deterministic and stochastic optimization techniques can be combined to infer knowledge on the functioning of a complex system, and explore its limits and potential.

The paper is organized as follows. In the next section, the model of the Red River Basin is described. This includes the definition of indicators to quantify and compare the impacts of alternative operating policies on the socio-economic system, and the model of the physical components, namely rivers and reservoir. In Sect. 3, the re-operation of the HoaBinh reservoir is discussed. To this purpose, stochastic optimization (specifically Multi-Objective Genetic Algorithms) is used. The indicators defined in Section 2 constitute the objective functions of the optimization problem, and the model of the physical system the constraints. In Sect. 4, the structural properties of the system, i.e. the upper bound of performances determined by the current storing capacity, is investigated by deterministic optimization (i.e. Deterministic Dynamic Programming). The major outcome of the study, the limitations and the topics for further research are summarized in the last section.

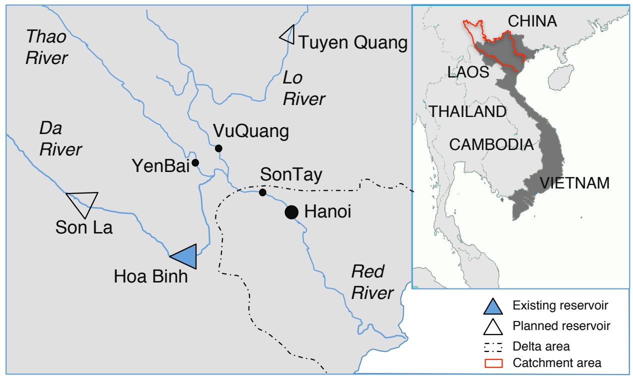


**Fig. 1.** The Red River Basin in Northern Vietnam.

## 2 System and models

The Red River Basin (Fig. 1) is the second largest basin of Vietnam, with a total area of about 169 000 $km^2$, of which 48 % in China's territory, 51 % in Vietnam, and the rest in Laos. Of three main tributaries, the Da River is the most important water source, contributing for 42 % of the total discharge at SonTay. The rainfall distribution is significantly uneven: rainfall of the rainy season, from May to October, accounts for nearly 80 % of the yearly amount, peaking in August (20 %).

Since 1989, the discharge from the Da River has been regulated by the operation of the HoaBinh reservoir. The construction of the dam started in 1979 and finished in 1989, while the filling of the reservoir was completed by 1994. With a storage capacity of 9.8 billion $m^3$, the HoaBinh reservoir is the largest reservoir in use in Vietnam and accounts for the 15 % of the national electricity production. The dam operation also contributes to flood control, especially to protect the region's capital city of Hanoi, and to water supply for irrigated agriculture in the Red River Delta.

### 2.1 The socio-economic system

Social and economic interests in the Red River basin are modeled through physical indicators that quantify the evaluation criteria that the relevant stakeholders adopt in judging and comparing alternative operating policies. The formulation and subsequent identification of these indicators should take into consideration some fundamental properties and concepts: (i) indicators are supposed to accurately reproduce the stakeholders viewpoints and should thus reflect their perception of the problem; (ii) they must meet some technical requirements imposed by the control algorithm adopted to design the operating policies. Precisely, the indicators must be formulated as the integral over a reference time horizon of immediate costs that should be, in turn, easily computable from the system model output without adding to much to the problem complexity. To balance fidelity and computational complexity, immediate costs are formulated as simple physical relationships including empirical parameters fitted to the stakeholder risk perception.

### 2.1.1 Hydropower production

The Vietnamese electricity market is regulated by the Government and the energy is sold at a fixed rate decided on the basis of the average energy production cost and the current economic development strategy. Electricity prices change depending upon the energy destination (industrial or domestic use) and the total energy consumed but not within the day or the week. In economic terms, given the fixed cost of hydropower generation, maximizing the energy production is equivalent to maximize the associated revenue. Yet, the fast-growing national energy demand (Toan et al., 2011) and the recently increasing frequency of power shortages in the last three months of the dry season, from April to June, make the smaller energy available in this period much more valuable than in others. To account for this seasonal variability, in formulating the immediate cost, the daily energy production $P_{t+1}$ [GWh] (see Eq. 5) is filtered by a time-varying coefficient $\alpha_t$, expressing the value given to one GWh on day $t$, i.e.

$$g_{t+1}^{\text{hyd}} = -\alpha_t \; P_{t+1}. \tag{1}$$

Based on the analysis of the energy deficit and the consequent import from China in the different seasons, $\alpha_t$ is assumed equal to 2 from April to June and 1 in the other months. Since the indicators are formulated as costs, the production in Eq. (1) is changed in sign.

### 2.1.2 Water supply

Wet-rice agriculture is key to national food security but also the most important segment of the Vietnamese economy (FAOSTAT, 2003). The optimal climatic conditions and plentiful water resources of this tropical monsoonal region enabled an intensive rice production in the Red River Delta (RRD), composed of 31 irrigation schemes servicing around 850 000 ha of irrigated agriculture (Turral and Chien, 2002) and forming the second largest rice production area in the country after the Mekong Delta. The maximization of the net crop return (including variable and fixed costs) is the economic indicator traditionally adopted by the wet-agriculture sector (e.g. see Kipkorir et al., 2001). However, both crop price and yield dynamics do require sophisticated models, which are not easily identifiable from conventional observational data and would considerably add to the computational burden of the problem. In addition, the extensive use of pumping stations in the RRD distribution network (George et al., 2003) implies substantial energy costs in operating the irrigation scheme that, however, are hardly estimable due to the lack of data (Harris, 2006). For these reasons, the average annual water deficit can be adopted as a proxy of the annual crop yield and the disaggregated daily deficit the corresponding immediate cost. This is a provably reasonable hypothesis under the assumption that the considered operating policies will not move to much away from the current average water supply (Soncini-Sessa et al., 2007a). Further, to make the surrogation more reliable, the annual deficit is not linearly reallocated on a daily basis, but modulated by a time-varying coefficient $\beta_t$ that accounts for the combined varietal phenological stages and climate conditions and the associated time-varying risk of stress (e.g. Kulshreshtha and Klein, 1989). Finally, farmers are not insensitive to the magnitude of the daily deficit since, the integral effect of water shortages being the same, several small deficits might be more acceptable than one single severe shortage that might strongly affect crop production (e.g. see Draper and Lund, 2004 and references therein). A behavioral coefficient $n$ is thus used to characterize farmers' risk aversion: $n = 1$ means no risk aversion, while for $n \to \infty$ the aversion is maximum and the indicator is equivalent to a min-max formulation (Soncini-Sessa et al., 2007b). Correspondingly, the immediate cost for the water supply is formulated as a power function:

$$g_{t+1}^{\text{sup}} = \begin{cases} 0 & \text{if } q_{t+1}^{\text{ST}} > w_t \\ \beta_t \left(w_t - q_{t+1}^{\text{ST}}\right)^n & \text{otherwise} \end{cases} \tag{2}$$

where $w_t$ and $q_{t+1}^{\text{ST}}$ [$\text{m}^3\,\text{s}^{-1}$] are the daily water demand and supply at SonTay (Fig. 1), and $\beta_t$ is equal to 2 from January to March, when the diverted flow from the Red River is the only source for the submersion of paddy fields for winter-spring rice crop, and 1 in the rest of the year when the submersion for the summer-autumn crop is additionally supported by rainfall.

### 2.1.3 Flood mitigation

Hanoi and its unusually overdeveloped river urban area (RUA) are protected by a system of two series of dykes for a total length of 2700 km. Floods mainly occur in July and August and inundations produce enormous damage every time dykes break (Hansson and Ekenberg, 2002), as regularly happened nearly once per decade in the last century. In principle, an accurate modelling of flood inundations and the associated damage requires to combine a 2D model of the floodplain to estimate the flooded surface area (e.g. Hoang et al., 2007) and a record of past flood recovery costs and associated river flow rates to interpolate the corresponding damage (e.g. De Kort and Booij, 2007). Because of the regularly disruptive effects of the flood routing process following a dyke breaching on the RUA morphology, any flood propagation model should be recalibrated after every flood event. Further, the fast uncontrolled urban development in the RUA is quickly changing the size and shape of the floodplain, thus making totally incomparable damages registered in different years.

Damages can thus not be included as an indicator in our decision model. Nevertheless, it is observable (Vorogushyn et al., 2010) that high and persisting flood water levels in Hanoi correspond to high risk of dike break, and consequently high potential damage. An indirect way of accounting for flood damage is thus to penalize operating policies that produce river water levels higher than some appropriately selected threshold. Once again, economic relevance and risk perception are implicitly accounted for using some empirical coefficients: the higher damage potential of floods in August on the summer-autumn crop (Le et al., 2007) is given a higher weight, while the increased stakeholders' risk aversion to extreme flood is modelled by using a power law. The resulting immediate cost has the following form:

$$g_{t+1}^{\mathrm{flo}} = \begin{cases} 0 & \text{if } h_{t+1}^{\mathrm{HN}} \leq \bar{h} \\ \delta_t \left(h_{t+1}^{\mathrm{HN}} - \bar{h}\right)^m & \text{otherwise} \end{cases} \tag{3}$$

where $h_{t+1}^{\mathrm{HN}}$ is the water level [cm] at Hanoi station, $\bar{h}$ (= 950 cm) is the 1st alarm flood level (Hansson and Ekenberg, 2002), $\delta_t$ is the seasonal coefficient (equals 2 in August and 1 otherwise), and $m$ is the coefficient reflecting risk aversion here assumed equal to 2. The rational is that flood risk comes from either the overtopping of the levees or the levee breaches. The latter are more likely to occur in August because the mean water level is 829 cm (against 453 cm in the rest of the year) and thus the soil volume of the water-saturated levee is larger. Water level excesses are thus given more weight in August. Further, the total force on the levee, which is the driver of collapse, increases with the square of the water level, which motivates the choice of power 2 in Eq. (3).

### 2.2 The physical system

The model of the Red River Basin is briefly described in this section, more details can be found in Quach (2011). It is composed of two main components: the model of the HoaBinh reservoir and hydropower plant, and the model of the river network downstream of the reservoir. A scheme of the model and the most relevant variables is given in Fig. 2.

#### 2.2.1 The HoaBinh reservoir

The HoaBinh reservoir is an artificial reservoir with a storage capacity of 9.8 billion m$^3$ and an active storage of 6 billion m$^3$, corresponding to a level operational range of 37 m. It has 8 penstoks, 12 bottom gates, and 6 spillways with maximum release capacity of 2360 m$^3$ s$^{-1}$, 22 000 m$^3$ s$^{-1}$, and 14 000 m$^3$ s$^{-1}$ respectively. The reservoir dynamics is modeled by daily mass balance equation considering inflow from the Da River catchment, evaporation and release:

$$s_{t+1} = s_t + q_{t+1}^{\mathrm{HB}} - e_{t+1}\, S(s_t) - r_{t+1} \tag{4}$$

where $s_t$ is the storage on day $t$, $q_{t+1}^{\mathrm{HB}}$ is the inflow to the HoaBinh reservoir (i.e. outflow of the Da catchment); $e_{t+1}$ is

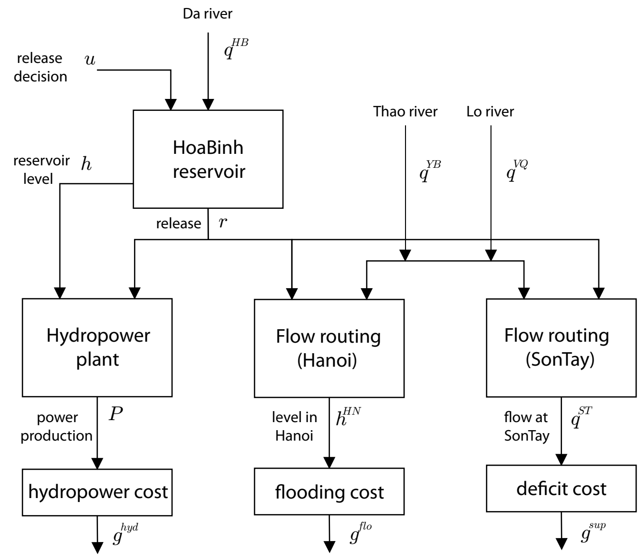


**Fig. 2.** The model scheme of the Red River Basin and the main system variables.

the unitary surface evaporation (which follows a yearly pattern); $S(\cdot)$ is the reservoir surface computed as a function of the storage; and $r_{t+1}$ is the release. The actual release $r_{t+1}$ coincides with the release decision $u_t$ only if the latter is feasible, i.e. included between the minimum and maximum feasible release that can be obtained when all the gates are completely closed or open, respectively. Such values are computed by integration of the continuous-time mass balance equation using the instantaneous minimum and maximum stage-discharge relation (Castelletti et al., 2008) as given by the rating curves of the turbines, bottom gates, and spillways.

Validation of the reservoir model is carried out by comparing the historical time series (level and release) and the simulated time series when using the reservoir model under historical inflow. Since the historical release decision is not known, simulation was run using the historical release as release decision. Still, the simulated trajectories might diverge from the historical ones because either the evaporation contribution in Eq. (4) or the feasibility constraints in computing the actual release (minimum and maximum feasible release) are not estimated properly. In our case study, simulation over the period 1994–2005 showed that the model is quite accurate, with simulated level and release almost coincident with historical ones.

The HoaBinh hydropower plant, located just downstream of the reservoir, has eight turbines with total installed capacity of 1920 MW. The daily energy production [GWh] is

$$P_{t+1} = \varphi\, g\, \gamma\, H_{t+1}\, \eta(H_{t+1})\, q_{t+1}^{\mathrm{turb}} \tag{5}$$

where $\varphi$ is a coefficient of dimensional conversion, $g$ is gravitational acceleration, $\gamma$ is water density, $H_{t+1}$ is the hydraulic head difference (depending on the reservoir and downstream level), $\eta(\cdot)$ is the turbine efficiency and $q_{t+1}^{\mathrm{turb}}$ is the flow through the turbines, given by

$$q_{t+1}^{\mathrm{turb}} = \begin{cases} 0 & \text{if } r_{t+1} \le q^{\min} \\ \min\left(r_{t+1},\, q^{\max}\right) & \text{otherwise} \end{cases} \tag{6}$$

where $r_{t+1}$ is the HoaBinh release, $q^{\max}$ is the maximum turbines capacity ($2360\,\mathrm{m^3\,s^{-1}}$), and $q^{\min}$ is the minimum release through the turbines ($38\,\mathrm{m^3\,s^{-1}}$) as inferred from historical data.

The model of the hydropower plant was validated by comparison of the energy production data over the period 1995–2004 and model simulations, using historical level and release data as the input to the plant model of Eqs. (5)–(6). The average annual energy production by the model is 7.82 TWh, against a historical value of 7.76 TWh, equivalent to a relative error of 0.77 %. The relative absolute error in the estimation of the daily production is much higher, about 11 %. However, the mismatch may be ascribed to the measurement errors in the release time series rather than to model inaccuracy.

#### 2.2.2 The downstream river network

Besides hydropower production, the release from HoaBinh reservoir also affects the total discharge at SonTay and the water level at Hanoi, which decide the extent of the water deficit in the dry season and flood risk in the flood season. Therefore, two downstream flow routing models, one for estimating the water level $h_{t+1}^{\mathrm{HN}}$ at Hanoi (the so-called Hanoi model) and the other for predicting the flow $q_{t+1}^{\mathrm{ST}}$ at SonTay (the so-called SonTay model), are needed (see Fig. 2). For both models, a data-driven approach based on a feedforward neural network was used. The network architecture comprises a hidden layer of $\nu$ hyperbolic tangent neurons, and an output layer of one linear neuron. For instance, the SonTay model takes up the form

$$q_{t+1}^{\mathrm{ST}} = \vartheta_1 + \sum_{i=1}^{\nu} \vartheta_{2,i} \operatorname{tansig}\Big(\vartheta_{3,i}\, r_{t+1} + \vartheta_{4,i}\, q_{t+1}^{\mathrm{YB}} + \vartheta_{5,i}\, q_{t+1}^{\mathrm{VQ}} + \vartheta_{6,i}\Big) \tag{7}$$

where $r_{t+1}$ is the release from the HoaBinh reservoir, $q_{t+1}^{\mathrm{YB}}$ and $q_{t+1}^{\mathrm{VQ}}$ are the flow from the two tributaries Thao and Lo; and $\vartheta_1$, $\vartheta_{2,i}$, ..., $\vartheta_{6,i}$ ($i = 1, ..., \nu$) are the network parameters.

Equation (7) defines an instantaneous, static relation between the upstream flows $r_{t+1}$, $q_{t+1}^{\mathrm{YB}}$, $q_{t+1}^{\mathrm{VQ}}$ and the network output (flow at SonTay/level in Hanoi). This is consistent with data analysis, which shows high cross-correlation between input and output variables at lag value 0, and with the study by Nguyen (2010), which states that the translation time from HoaBinh reservoir, Yenbai, and Vuquang to SonTay and Hanoi is less than one day. However, adding lagged values of upstream flows among the network inputs can improve the model accuracy. This was not done in the present study because of the need of finding a balance between model accuracy and model complexity, which may prevent the application of dynamic optimization methods like Deterministic Dynamic Programming (see Sect. 4), whose computational complexity increases exponentially with the number of state variables in the global model, not only in the reservoir model.

The optimal number $\nu$ of neurons in Eq. (7) was estimated by trial and error. For each tested number of neurons, the network parameters were estimated by minimization of the squared deviations from observed flow at SonTay (or level in HaNoi). The calibration dataset covers the period 1989–2004, which includes the simulation horizon (1995–2004) that will be used as the testing ground for the different reservoir operating policies. With this choice, it can be guaranteed that the flow-routing process is optimally reproduced for the time horizon of interest, even if the model accuracy outside of this period is not known. In fact, river bed erosion that started after the construction of the HoaBinh reservoir may be affecting the statistical relation between flow variables in the river network in the future. Consequently, the evolution of such relation cannot be predicted by a model that does not explicitly take into account erosion and aggradation processes. While we have information that such processes are undergoing, we do not have enough data to develop a model to accurately reproduce them. So, the most that can be done is to use historical time series and calibrate a model that can adequately reproduce the flow routing process over the past. Obviously, both the model and the operating policies that will be subsequently designed may prove suboptimal if applied in the future, under changed geomorphological conditions. However, the main objective of this paper, i.e. to assess the space for improvement of the historical operation, is not affected by this limitation, since all operating policies are evaluated by the same model, and this is optimally calibrated for the evaluation horizon under exam. Further, the simulation and optimization tools here proposed and demonstrated can be re-applied in the future as new data become available.

Table 1 reports several performance indicators of the optimally calibrated downstream model (with $\nu = 8$ neurons for the Hanoi model and $\nu = 6$ for the SonTay model). Some are standard accuracy indicators like the coefficient of determination and the maximum absolute error, computed over the period 1995–2004 (lines 1, 2 in the table) or over the subset of low flows and high levels (lines 3 and 4). The other indicators are more focused on the final scope of our modelling exercise, that is to estimate the shortage in the water supply at SonTay and the exceedance of the flooding threshold in Hanoi (950 cm). Specifically, the 5th indicator is the average value of the immediate costs (Eqs. 2 and 3) associated to the water supply and flood control objective, respectively. The table shows that although the two downstream models are generally quite accurate, the SonTay model does not perform very well on low flow values (see lines 3 and 4), which reflects into a significant underestimation of the water supply

**Table 1.** Performance indicators of the downstream models (His: historical data; ST: SonTay model; HN: Hanoi model) over the period 1995–2004.

| | Indicators | Unit | His | ST |
|---|---|---|---|---|
| 1 | $R^2$ (coefficient of determination) | – | 1 | 0.956 |
| 2 | MAE (maximum absolute error) | $m^3\,s^{-1}$ | 0 | 3986 |
| 3 | $R^2$ ($q < 1046\,m^3\,s^{-1}$) | – | 1 | 0.662 |
| 4 | MAE ($q < 1046\,m^3\,s^{-1}$) | $m^3\,s^{-1}$ | 0 | 136 |
| 5 | Avg. daily weighted squared deficit | $(m^3\,s^{-1})^2$ | 1728 | 887 |
| 6 | Avg. yearly deficit | $(m^3\,s^{-1})\,yr^{-1}$ | 902 | 737 |
| 7 | Avg. no of days of deficit per year | days $yr^{-1}$ | 4 | 5.6 |
| 8 | Max consecutive days of deficit | days $yr^{-1}$ | 28 | 22 |
| | **Indicators** | **Unit** | **His** | **HN** |
| 1 | $R^2$ (coefficient of determination) | – | 1 | 0.985 |
| 2 | MAE (maximum absolute error) | (cm) | 0 | 21 |
| 3 | $R^2$ ($h > 950$ cm) | – | 1 | 0.805 |
| 4 | MAE ($h > 950$ cm) | (cm) | 0 | 23 |
| 5 | Avg. daily weighted squared exceedance | $(cm)^2$ | 890 | 902 |
| 6 | Avg. yearly exceedance | cm $yr^{-1}$ | 1430 | 1503 |
| 7 | Avg. no of days of $h > 950$ cm per year | days $yr^{-1}$ | 16 | 16 |
| 8 | Max consecutive days of $h > 950$ cm | days | 19 | 18 |

immediate cost indicator (line 5) and might undermine the comparison between historical and simulated performances. To overcome the problem, from now on when referring to the historical system performances we will not refer to the historical data of deficit in the water supply (and hydropower production and flood objective) but rather to the indicator values computed by our model when fed by historical data of Thao and Lo flows and HoaBinh storage and release (see Fig. 2).

## 3 Re-operation of the HoaBinh reservoir by MOGA

After modelling the system, the subsequent step of our study is to analyze the historical operation of the HoaBinh reservoir. The analysis of the available data, from 1995 (the date when the reservoir filling can be considered completed) to 2004, shows that the HoaBinh reservoir was operated according to a seasonal strategy. From January to June the reservoir release ranges from 500 to 2000 $m^3\,s^{-1}$, which is generally enough to support the water supply at SonTay. In fact, the water demand is not satisfied only 56 days in these 11 yr. In this period, the reservoir release is generally higher than the natural flow of the Da River and, correspondingly, the HoaBinh level decreases of about 25–30 m in six months (see top panel in Fig. 3). The decrease in the HoaBinh level is favorable for flood control as the reservoir reaches its minimum level just by the beginning of June, in anticipation of the floods that may occur in July and especially August. From September to October, as the threat of floods diminishes, the reservoir is refilled and by the beginning of November the full capacity, and thus the maximum hydraulic head, is reached again. Notice that on the 1 November, when the transition from the wet to the dry season takes place, the HoaBinh reservoir is always at full capacity, whereas at the dry-to-wet transition (1 June), the HoaBinh level varies between 77.5 and 96.2 m depending on the year, meaning that occasionally water is transferred from one season to the other, in order to maintain the hydraulic head as high as possible. It follows that, while it is possible to simulate and optimize the system management over one year starting from the 1 November with the storage at full capacity, disconnecting the dry and wet season on the 1 June would unnecessarily limit the potential for optimizing the storage value at the transition. This point will be confirmed also in the following simulation results under optimized operating policies.

The first question addressed by our study is whether the application of optimal control would have improved the system performances over the evaluation horizon 1995–2004. Precisely, our goal is to design one or more operating rules that prove Pareto-dominant over the historical operation. To this purpose, we used Multi-Objective Genetic Algorithms (MOGA), which are an effective and rather simple-to-apply method for multi-objective stochastic optimization (for application of MOGA to reservoir operation see Oliveira et al. (1997) or Pianosi et al. (2011); for a review of other reservoir optimization methods, see Labadie (2004) or Castelletti et al. (2008)). The idea is to select a suitable function

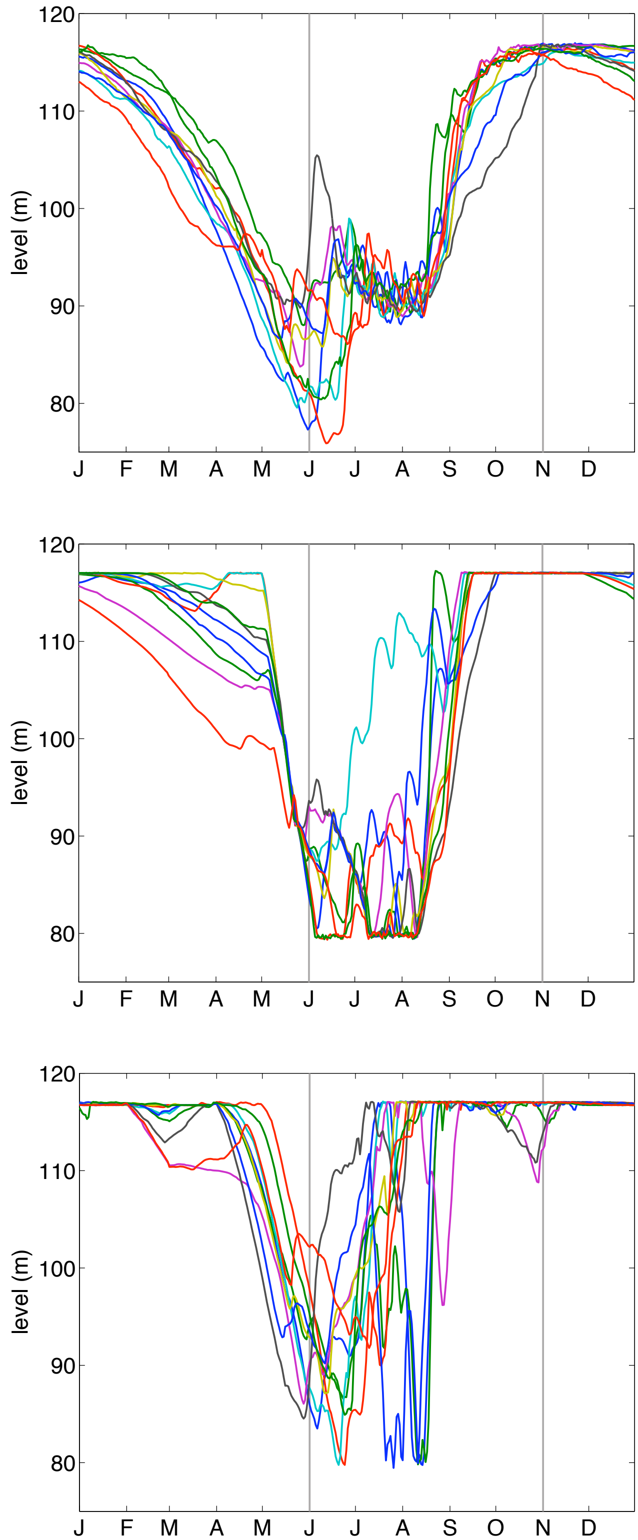


**Fig. 3.** Yearly pattern of the HoaBinh level with historical operation (top panel), MOGA-19 policy (middle panel) and DDP-21 (bottom panel) over the evaluation horizon 1995–2004.

family for the operating rule and apply MOGA to determine the function parameters that minimize the average value of the immediate costs (Eqs. 1, 2, 3) over a given horizon. In this study, we selected Artificial Neural Network as function family, since they guarantee high flexibility at low complexity (and thus a small number of parameters to be optimized). The release decision $u_t$ is thus given by

$$u_t = \theta_0 + \sum_{j=1}^{\mu} \theta_{1,j} \text{ tansig } \big(\theta_{2,j}\, s_t + \theta_{3,j} \cos\,(2\,\pi/T\ t)$$

$$+ \theta_{4,j} \sin\,(2\,\pi/T\ t) + \theta_{5,j}\big) \tag{8}$$

where the network inputs are the reservoir storage $s_t$ and the time index $t$, $T = 365$ (days) is the system's period of cyclostationarity, $\mu$ is the number of tangent sigmoid neurons in the hidden layer, and $\theta_0, \theta_{1,j}, ..., \theta_{5,j}$ $(j = 1, ..., \mu)$ are the network parameters. The three-objective optimization problem is

$$\min_{\boldsymbol{\theta}} \left[ \frac{1}{h} \sum_{t=0}^{h-1} g_{t+1}^{\text{hyd}},\ \frac{1}{h} \sum_{t=0}^{h-1} g_{t+1}^{\text{sup}},\ \frac{1}{h} \sum_{t=0}^{h-1} g_{t+1}^{\text{flo}} \right] \tag{9}$$

where $t = 0$ and $t = h-1$ are the first and last day in the optimization horizon; $g_{t+1}^{\text{hyd}}$, $g_{t+1}^{\text{sup}}$ and $g_{t+1}^{\text{flo}}$ are the immediate costs defined in Sect. 2.1, whose value is computed as a function of the parameters $\boldsymbol{\theta} = |\theta_0, \theta_{1,1}, ..., \theta_{5,\mu}|$ of the operating rule (Eq. 8) by simulation of the model described in Sect. 2.2.

In MOGA, each candidate solution $\boldsymbol{\theta}$ to problem (Eq. 9) is regarded as the genome ("chromosome") of an "individual". MOGA starts from a randomly selected population of $N$ "individuals". The "fitness" (average value of the immediate costs) of each individual is tested by simulation of the system under historical flows of the upper Da, Thao and Lo River and the operating policy (Eq. 8) where $\boldsymbol{\theta}$ is the individual's "chromosome". Then, a new population is generated by selection, crossover and mutation, and the process is repeated for a prescribed number of iterations. In this study, selection, crossover and mutation are performed according to the Non-dominated Sorting Genetic Algorithm NSGA II (Deb et al., 2002), while the selection of the initial population relies on ideas by Pianosi et al. (2011). Notice that under this approach, observed flows are used for system simulation but they are not exploited in the operating rule, which uses the minimum information (storage and time) that is actually available to the manager in real-world.

To make a fair comparison with historical operation, in the optimization process the system simulation uses historical discharges over the period 1957–1978 (optimization horizon) and the final population is then re-simulated over the period 1995–2004 (evaluation horizon). Table 2 reports the average value of the three immediate costs over such horizon with an ANN with $\mu = 6$ neurons (population size of 600 individuals evolved for 2000 iterations; results in the table refer to the subset of solutions that proved Pareto-dominant over

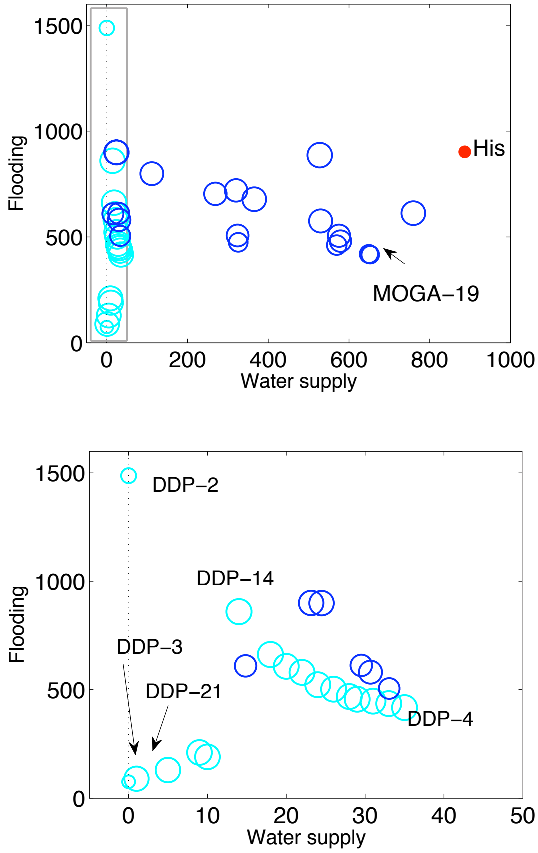


**Fig. 4.** Top panel: average value of the immediate costs over the horizon 1995–2004 under historical operation (red), operating policies optimized by MOGA (blue) and by DDP (cyan). Bottom panel: zoom of the box in the top panel.

**Table 2.** MOGA results: average value of the immediate costs under different network parameterizations with 6 neurons (evaluation horizon 1995–2004).

| Policy | hyd GWh | sup $(m^3\,s^{-1})^2$ | flo $cm^2$ |
|---|---|---|---|
| History | −26.3 | 887 | 902 |
| MOGA-1 | −31.7 | 24 | 899 |
| MOGA-2 | −30.0 | 33 | 506 |
| MOGA-3 | −30.7 | 324 | 507 |
| MOGA-4 | −30.9 | 575 | 506 |
| MOGA-5 | −31.3 | 530 | 576 |
| MOGA-6 | −30.4 | 30 | 612 |
| MOGA-7 | −31.0 | 269 | 704 |
| MOGA-8 | −32.0 | 528 | 886 |
| MOGA-9 | −31.7 | 23 | 900 |
| MOGA-10 | −30.5 | 579 | 481 |
| MOGA-11 | −30.3 | 15 | 610 |
| MOGA-12 | −29.3 | 326 | 475 |
| MOGA-13 | −31.6 | 759 | 613 |
| MOGA-14 | −31.6 | 365 | 679 |
| MOGA-15 | −31.0 | 320 | 720 |
| MOGA-16 | −28.8 | 653 | 417 |
| MOGA-17 | −31.0 | 31 | 581 |
| MOGA-18 | −31.2 | 112 | 799 |
| MOGA-19 | −29.1 | 649 | 420 |
| MOGA-20 | −29.6 | 570 | 462 |

the historical operation). They are also represented in the top panel of Fig. 4 by the blue circles. Here, the circle size is proportional to the average hydropower cost (Eq. 1) changed in sign (so, the bigger the marker the higher the hydropower production). The red circle refers to the historical performance estimated by model simulation under historical flows (see discussion in Sect. 2.2). Cyan circles will be discussed in the next section.

All the reported MOGA solutions are Pareto-dominant over the historical operation and Pareto-efficient among each other. From the hydropower production standpoint, the best solution is MOGA-8, whose energy design indicator is −32.0 (historical value is −26.3). According to Eq. (1) this figure represents the average daily production differently weighted depending on the season; the corresponding average annual production is 8.35 TWh per year (historical value is 7.82). The performances in terms of water supply and flood control are just slightly better than historical. From the water supply standpoint, several solutions (e.g. MOGA-1, 2, 6, 9, 11, 17) provide very good performances, reducing the water shortage to almost zero while maintaining a high hydropower production and sligthly reducing floods in Hanoi. Other solutions, e.g. MOGA-16 and 19, are better for flood control at the price of a more limited improvement for the other two objectives.

The analysis of the system trajectories provides more insights about the MOGA solutions. For instance, the middle panel in Fig. 3 shows the yearly pattern of the HoaBinh level produced by MOGA-19. It shows that MOGA-19 uses a seasonal strategy similar to the historical operation (top panel) but it can keep the reservoir at full capacity (117 m) for a longer period, which increase the hydraulic head and thus hydropower production. Figure 5 compares the water level in Hanoi during the 1996 flood under the historical operation (red) and the MOGA-19 policy (blue). It can be seen that MOGA-19 can reduce the first level peak in July (from 10.6 to 9.78 m) and reduce the duration of the second flooding in August (from 13 to 8 days above the flooding threshold of 9.5 m). Although the improvement with respect to the historical operation is significant, there seems to exists large space for further improvement of the operating policy in terms of flood control. Now the question arises whether better policies for flood control were not found due to structural constraints (the storing capacity is not sufficient to completely control floods in Hanoi) or to an imperfect information system (the inputs to the operating rule are not sufficient

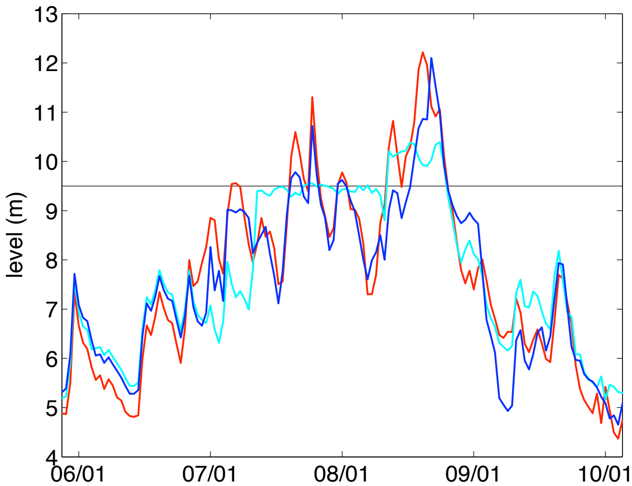


**Fig. 5.** Water level in Hanoi in the 1996 flood season (June to September) under historical operation (red), MOGA-19 policy (blue) and by DDP-21 (cyan). The black line is the flooding threshold in Hanoi.

to anticipate the flood and react properly). This question will be addressed in the next section.

## 4 Assessing the upper bound of system performances by DDP

To assess the loss in performances due to the system physical limits and the contribution from limited forecasting capacity, we run a final simulation experiment assuming perfect information system, that is, full knowledge of all future flows from the upper Da River and the tributaries Lo and Thao. The associated upper bound of performances can be derived by solving a deterministic optimal control problem, i.e. finding the trajectory of release decisions (release scheduling) $\boldsymbol{u} = |u_0, u_1, ..., u_{h-1}|$ that minimizes the average aggregate cost under historical flow pattern of the Da, Thao and Lo River. The (single-objective) deterministic control problem is

$$\min_{\boldsymbol{u}} \left( \lambda_1 \frac{1}{h} \sum_{t=0}^{h-1} g_{t+1}^{\mathrm{hyd}} + \lambda_2 \frac{1}{h} \sum_{t=0}^{h-1} g_{t+1}^{\mathrm{sup}} + \lambda_3 \frac{1}{h} \sum_{t=0}^{h-1} g_{t+1}^{\mathrm{flo}} \right) \tag{10}$$

where $t = 0$ and $t = h - 1$ are the first and last day in the optimization horizon; $g_{t+1}^{\mathrm{hyd}}$, $g_{t+1}^{\mathrm{sup}}$ and $g_{t+1}^{\mathrm{flo}}$ are the immediate costs defined in Sect. 2.1, whose value is computed as a function of the release scheduling $u$ by simulation of the model described in Sect. 2.2; and $\lambda_1$, $\lambda_2$, $\lambda_3$ are the aggregation weights. For a given combination of weights, the associated single-objective problem (Eq. 10) can be solved by Deterministic Dynamic Programming (DDP). By changing the weight values, different tradeoffs between the objectives are defined and the Pareto-optimal solutions are found.

To exclude the effects of the boundary conditions, the optimization horizon is larger than the evaluation horizon

**Table 3.** DDP results: average value of the immediate costs under different weight combinations (evaluation horizon 1995–2004).

| Policy | $\lambda_1$ | $\lambda_2$ | $\lambda_3$ | hyd GWh | sup $(\mathrm{m^3\,s^{-1}})^2$ | flo $\mathrm{cm}^2$ |
|---|---|---|---|---|---|---|
| History | – | – | – | −26.3 | 887 | 902 |
| DDP-1 | 1.000 | 0.000 | 0.000 | −32.1 | 10 083 | 1927 |
| DDP-2 | 0.000 | 1.000 | 0.000 | −27.4 | 0 | 1487 |
| DDP-3 | 0.000 | 0.000 | 1.000 | −26.4 | 0 | 75 |
| DDP-4 | 0.100 | 0.460 | 0.440 | −31.9 | 35 | 417 |
| DDP-5 | 0.100 | 0.490 | 0.410 | −31.9 | 33 | 436 |
| DDP-6 | 0.100 | 0.520 | 0.380 | −31.9 | 31 | 447 |
| DDP-7 | 0.100 | 0.540 | 0.360 | −31.9 | 29 | 456 |
| DDP-8 | 0.100 | 0.550 | 0.350 | −31.9 | 28 | 468 |
| DDP-9 | 0.100 | 0.580 | 0.320 | −31.9 | 26 | 502 |
| DDP-10 | 0.100 | 0.610 | 0.290 | −31.9 | 24 | 523 |
| DDP-11 | 0.100 | 0.640 | 0.260 | −31.9 | 22 | 580 |
| DDP-12 | 0.100 | 0.670 | 0.230 | −31.9 | 20 | 608 |
| DDP-13 | 0.100 | 0.700 | 0.200 | −32.0 | 18 | 662 |
| DDP-14 | 0.100 | 0.800 | 0.100 | −32.0 | 14 | 860 |
| DDP-15 | 0.050 | 0.450 | 0.500 | −31.8 | 10 | 190 |
| DDP-16 | 0.030 | 0.480 | 0.490 | −31.7 | 5 | 129 |
| DDP-17 | 0.010 | 0.490 | 0.500 | −31.6 | 1 | 89 |
| DDP-18 | 0.010 | 0.290 | 0.700 | −31.6 | 2 | 84 |
| DDP-19 | 0.005 | 0.445 | 0.550 | −31.5 | 0 | 80 |
| DDP-20 | 0.005 | 0.195 | 0.800 | −31.5 | 2 | 78 |
| DDP-21 | 0.001 | 0.099 | 0.900 | −31.4 | 0 | 75 |

(1995–2004). Precisely, the optimization horizon starts some months earlier (1 November 1994) so that the indicator values are not affected by the initial storage value, and ends one year later (31 December 2005) to cut off the impact of the penalty over the final system state, which in Eq. (10) is implicitly set to zero for all possible storage values, as if it were indifferent in ending up at time $t = h$ with the HoaBinh completely full or empty or any value in between. The assumption is obviously incorrect, and during optimization it brings to selecting release schedulings that overexploit the available storage as the end of the optimization horizon approaches.

The average value of the three immediate costs over the evaluation horizon are displayed in Table 3 and represented by cyan circles in Fig. 4. It is seen that if only power production is considered (DDP-1), the value of energy design indicator is −32.1, slightly better than the best MOGA solution for hydropower (MOGA-8) and definitely lower than history. However, the immediate costs of deficit and flood are worse. The policy optimized for water supply only (DDP-2) can completely avoid water shortages (the average cost is zero), while the policy optimized for flood control (DDP-3) produces an average cost of 75. The other solutions in the table consider more than one objective at the time and produce different tradeoffs. Two groups of solutions can be distinguished. Policies from DDP-4 to DDP-14 produce flood and water supply costs similar to those of MOGA (see also bottom panel of Fig. 4) while producing more hydropower. Policies from DDP-15 to DDP-21 produce slightly less hydropower but can dramatically improve flood control. Also notice that under the (ideal) deterministic assumption, the conflict among objectives is mild, and solutions exist, e.g. DDP-21, that are very close to the Utopia point (−32.1, 0, 75).

The yearly pattern of the HoaBinh level produced by DDP-21 is plotted in the bottom panel in Fig. 3. Again, a seasonal pattern can be clearly seen, though the water level in the flood season (June–August) is generally higher because DDP exploits the perfect knowledge of future flows to reduce the reservoir level just in anticipation of the flood events, while the historical and MOGA operations keep the reservoir level low also in those years when floods did not occur. Finally, Fig. 5 compares the water level in Hanoi during the 1996 flood under historical operation (red), MOGA-19 (blue) and DDP-21 (cyan). It can be seen that DDP-21 can keep the water level below the threshold during the first flood peak and significantly reduce the peak level during the second, however the flooding cannot be completely avoided even with perfect knowledge of all future flows. In fact, the minimum average cost for the flood objective under DDP is not zero but 75.

To understand the reason, we ran a simulation of the downstream model setting the release from the HoaBinh to zero for all time instants, i.e. as if the Da River and HoaBinh reservoir did not exist. Figure 6 shows the scatter plot of water levels at Hanoi under this assumption and with HoaBinh releases under DDP-21. It shows that (i) some flood events in Hanoi occurring under solution DDP-21 are in fact produced by HoaBinh releases since they would not occur if the releases were zero (box A); (ii) some flood events would occur even if the release of the HoaBinh reservoir were zero (box B). In the former case, flooding is not avoided because of limited storing capacity of the HoaBinh reservoir, in the latter, flooding does not depend on the HoaBinh release but it is caused by the uncontrolled Lo and Thao tributaries. The result is consistent with the policy undertaken by the Vietnamese Government to expand the storing capacity by two new reservoirs (see Fig. 1): the SonLa reservoir upstream of the HoaBinh reservoir, which will increase the storing capacity along the Da River, and the TuyenQuang reservoir on the Lo River, completed in 2009, which allows for regulation of the discharge from that tributary too.

## 5 Conclusions

The paper presents an application of stochastic (MOGA) and deterministic (DDP) optimization methods to analyze the tradeoff between hydropower production, flood control and water supply in the Red River Basin, the second largest basin of Vietnam, and explore the room for improvement of the current management of the main infrastructure in the basin, the HoaBinh reservoir.

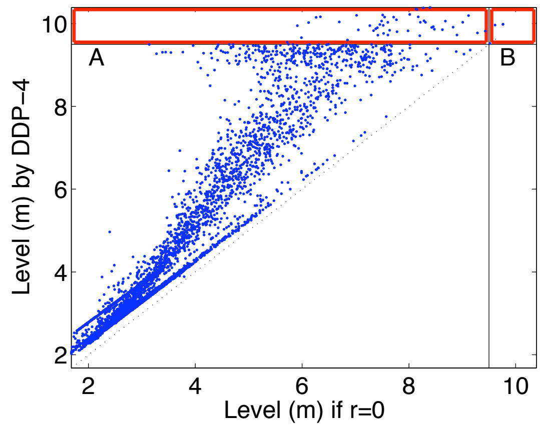


**Fig. 6.** Water level at Hanoi when the HoaBinh release is permanently equal to zero (horizontal axis) and produced by DDP-21 (vertical axis).

Results show that current reservoir operation can be consistently improved with respect to all three objectives. Several operating policies were found by MOGA that would have improved the historical system performances over the evaluation horizon from 1995 to 2004 for different tradeoffs. In general, hydropower production can be significantly increased and water shortages almost completely avoided; floods in Hanoi may also be reduced but at the price of a more limited improvement in the other two objectives. The analysis of one of the MOGA policy, chosen among the most favourable to the flood control objective, shows that the magnitude and duration of flooding in Hanoi (measured in terms of exceedence of the water level threshold) can be reduced while producing about 8.35 TWh per year (historical value being 7.82 TWh per year). Further research should be devoted to more accurately evaluate the improvement obtained on the water supply objective and the relatively mild conflict with the other operation objectives. This positive result might need to be confirmed when new data becomes available to improve the accuracy of the nominal water demand and the flow routing model of the downstream river network, possibly testing more complex flow routing models.

The operating policies proposed in this paper consider only reservoir storage and time of the year, i.e. the minimum possible information. Further improvement, especially on flood control, may be expected if a larger information system is adopted, e.g. including lagged flow values, meteorological observations or flow forecast. To assess the upper bound of this improvement we design the optimal operation of the system assuming perfect information is available. To this end, we applied DDP to design several operating policies under the ideal assumption of perfect knowledge of all future flows. Results show that all three objectives can be further improved with respect to the policies designed by MOGA and especially flood control. However, even under this ideal assumption, flooding in Hanoi could not be completely avoided. To understand the reason, we analyzed the contribution to flood formation from the different tributary rivers and demonstrate that, depending on the flood event, limited flood control ability may be due to insufficient storage capacity in the HoaBinh reservoir or unregulated flow from other tributaries in the RRB, which motivates for the construction of new reservoirs upstream of the HoaBinh and on other rivers.

Further research should also include analysis of the impacts of existing and planned reservoirs on other issues further to the three objectives considered in this study. Especially, the impacts of reservoirs on downstream flow regime and thus geomorphology and ecohydrology, including the erosion processes and ecosystem conservation issues, would deserve further investigation.

*Acknowledgements.* The authors would like to thank the Institute of Water Resource Planning-Hanoi-Vietnam, especially Phung Nguyen and Nam Le Hung, for providing the data of the HoaBinh water system.

Edited by: D. Solomatine

## References

Castelletti, A., Pianosi, F., and Soncini-Sessa, R.: Water reservoir control under economic, social and environmental constraints, Automatica, 44, 1595–1607, 2008.

De Kort, I. A. T. and Booij, M. J.: Decision making under uncertainty in a decision support system for the Red River, Environ. Modell. Softw., 22, 128–136, 2007.

Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T.: A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE T. Evolut. Comput., 6, 182–197, 2002.

Draper, A. J. and Lund, J. R.: Optimal Hedging and Carryover Storage Value, J. Water Res. Pl.-ASCE, 130, 83–87, 2004.

FAO: FAOSTAT Database, Food and Agriculture Organization, http://faostat.fao.org, last access: 13 July 2011, Rome, Italy, 2003.

George, B., Malano, H., and Chien, N.: System wide water management in the Dan Hoai irrigation scheme, Vietnam, in: International Commission on Irrigation and Drainage (ICID) 2nd Asian Regional Conference, Melbourne, 2003.

Hansson, K. and Ekenberg, L.: Flood mitigation strategies for the Red River Delta, in: International Conference on Environmental Engineering, An International Perspective on Environmental Engineering, Canada, 2002.

Harris, D.: Water management in public irrigation schemes in Vietnam, Canberra, Australia, 2006.

Hashimoto, T., Stedinger, J. R. S., and Loucks, D. P.: Reliability, resilience, and vulnerability criteria for water resource system performance evaluation, Water Resour. Res., 18, 14–20, 1982.

Hoang, V., Shaw, R., and Kobayashi, M.: Flood risk management for the RUA of Hanoi, Disaster Prev. Manage., 16, 245–258, 2007.

Hoang, V., Shaw, R., and Kobayashi, M.: Flood risk management for the riverside urban areas of Hanoi: The need for synergy in urban development and risk management policies, Disaster Prev. Manage., 19, 103–118, 2010.

Kipkorir, E. C., Raes, D., and Labadie, J.: Optimal Allocation of Short-Term Irrigation Supply, Irrig. Drain. Syst., 15, 247–267, doi:10.1023/A:1012731718882, 2001.

Kulshreshtha, S. N. and Klein, K. K.: Agricultural drought impact evaluation model: A systems approach, Agr. Syst., 30, 896, doi:10.1016/0308-521X(89)90083-8, 1989.

Labadie, J.: Optimal operation of multireservoir systems: state-of-the-art review, Water Resour. Pl. Manage., 130, 93–111, 2004.

Le, L., Tran, T., and Phan, H.: Project of integrated water resource management in the Red-ThaiBinh River basin, Report on hydrology, Hydrological report 1, Institute of Water Resources Planning, Hanoi, 2007.

Ngo, L. L., Madsen, H., and Rosbjerg, D.: Simulation and optimization modelling approach for operation of HoaBinh reservoir in Vietnam, J. Hydrol., 2007, 269–281, 2007.

Ngo, L. L., Madsen, H., Rosbjerg, D., and Pedersen, C. B.: Implementation and comparison of reservoir operation strategies for the HoaBinh reservoir, Vietnam using the Mike 11 model, Water Resour. Manage., 22, 457–472, 2008.

Nguyen, M.: Tree-based input selection for hydrological modelling, Master's thesis, Politecnico di Milano, 2010.

Nguyen, T., Do, N., Nguyen, T., and Egashira, K.: Agricultural development in the Red River delta, Vietnam – Water management, land use, and rice production, J. Fac. Agr. Kyushu U., 46, 445–464, 2002.

Oliveira, R. and Loucks, D. P.: Operating rules for multireservoir systems, Water Resour. Res., 33, 839–852, doi:10.1029/96WR03745, 1997.

Pianosi, F., Quach Thi, X., and Soncini-Sessa, R.: Artificial Neural Networks and Multi Objective Genetic Algorithms for water resources management: an application to the HoaBinh reservoir in Vietnam, in: Proceedings of the 18th IFAC World Congress, Milan, I, 2011.

Quach, X.: Assessing and optimizing the operation of the HoaBinh reservoir, Vietnam, by multi-objective optimal control techniques, Ph.D. thesis, Politecnico di Milano, 2011.

Soncini-Sessa, R., Castelletti, A., and Weber, E.: Integrated and participatory water resources management, Theory, Elsevier, Amsterdam, 2007a.

Soncini-Sessa, R., Cellina, F., Pianosi, F., and Weber, E.: Integrated and participatory water resources management, Practice, Elsevier, Amsterdam, 2007b.

Toan, P., Bao, N., and Dieu, N.: Energy supply, demand, and policy in Viet Nam, with future projections, Energy Policy, 39, 6814–6826, 2011.

Turral, H., Malano, H., and Chien, N. V.: Development and specification of a service agreement and operational rules for La Khe irrigation system, Ha Dong, Vietnam, Irrig. Drain., 51, 129–140, doi:10.1002/ird.48, 2002.

Vorogushyn, S., Merz, B., Lindenschmitdt, K. E., and Apel, H.: A new methodology for flood hazard assessment considering dike breaches, Water Resour. Res., 46, 1–17, 2010.