Optimization–simulation for short-term reservoir operation under flooding conditions

Babak Bayat, S. Jamshid Mousavi and Masoud Montazeri Namin

ABSTRACT

The problem of optimal operation of river–reservoir systems under flooding conditions is formulated in this study as a combination of particle swarm optimization (PSO) algorithm and a simulation model of river flood routing. Both hydrologic (Muskingum and Muskingum-Cunge) and hydraulic (solving Saint-Venant equations) flow routing methods are linked to the PSO algorithm with the objective function of minimizing flood damage in downstream areas. The Preissmann method is used to numerically solve the continuity and momentum equations. The developed optimization–simulation models were first tested in the case study of flood control operation of Bishop Dam, a benchmark problem in HEC-5 software. The models' performance was verified through their ability to reduce peak discharge at downstream control points compared to that resulting from applying gate regulation curve (GRC) operation policies available in HEC-5. Then the PSO-Venant model was used in the river–reservoir system of Upper Gotvand dam, a real case study in south-west Iran. Results show the significance of the model in determining optimal reservoir releases and minimizing flood damages.

Key words | flood routing, optimization, particle swarm optimization, reservoir operation

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INTRODUCTION

A prominent aspect of flood management is how to operate flood control reservoir systems during floods. Short-term reservoir operation deals with making decisions on future short-time interval (from a few minutes to a few hours) reservoir releases. Simulation and optimization models have been widely used in solving this problem. Examples of works based on simulation technology are the models developed by the US Army Corps of Engineers including HEC-5 (USACE 1998) and HEC-ResSim (USACE 2007), which are capable of simulating operations of reservoir systems with flood control, hydropower and water supply objectives, Colon & McMahon (1987), Ford & Killen (1995) and Ahmad & Simonovic (2000). Karbowski *et al*. (2005) proposed a combinatory analytical-rule based method for hourly operation of a reservoir system minimizing damages caused by high water elevations at control points.

Regarding optimization and optimization–simulation models, Hsu & Wei (2007) developed a real-time reservoir operation optimization model with the objectives of maximizing reduction of peak discharge at downstream control points during typhoons and optimizing end-of-flood reservoir storage volume. Unver & Mays (1990) developed a flood operation model of river–reservoir systems by integrating a nonlinear programming model and a flood routing simulation model. Ahmed (2006) linked a simulated annealing-based optimization algorithm to an unsteady full dynamic flow routing model for determining optimal reservoir releases under flooding conditions. Ngo (2006) developed a framework to connect a simulation model to a numerical search method for optimizing reservoir releases during floods. Madsen *et al*. (2006) accomplished real-time optimal reservoir operation by forecasting reservoir elevation data, inflow and water demands in order to improve Ngo's work in terms of operating conditions. Ngo *et al*. (2007) proposed a method of optimizing control policies of a reservoir system through combining simulation

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and optimization techniques. The model considers interchange between flood control objectives and hydropower generation in wet seasons as well as reservoir water elevation at the beginning of a dry season. Malekmohammadi *et al*. (2009) developed an optimization–simulation model for flood management in river–reservoir systems where a genetic algorithm (GA) was linked to HEC-RAS to perform a hydraulic-based flood routing model of downstream river system in a geographical information system (GIS) database.

Studies on flood control operation of reservoirs often concentrate on using simulation models or a combination of hydrologic routing simulation and classic optimization models. Moreover, little attention has been devoted to comparison of hydrologic and hydraulic routing methods within an optimization–simulation model framework. This paper aims to integrate the meta-heuristic algorithm of particle swarm optimization (PSO) with flow routing models. The application of different hydraulic and hydrologic routing models in short-term optimal operation of river–reservoir systems is also compared and contrasted.

Firstly, this paper describes the structures of the proposed optimization–simulation models and their formulation as well as the solution approach. The simulation models of flow routing including both hydrologic and hydraulic routing models are explained briefly and the PSO algorithm as the optimization module of the models is presented. The application of the models in two cases, the Bishop Dam reservoir operation, a benchmark problem used in HEC-5, and the Upper Gotvand river–reservoir system operation, a real case study in Iran, are discussed next. Finally, a summary and conclusion ends the paper.

OPTIMIZATION–SIMULATION MODEL

Although simulation models can provide an exact representation of hydrosystems operations, they may not be efficient in determining the optimal system design; optimization–simulation models, linking an existing simulation model to optimization algorithms are advantageous, as they incorporate both simulation and optimization approaches. In a river–reservoir system under flooding conditions, a flow simulation model considering physical constraints of the system operation can be integrated with an optimization model, where the best set of reservoir releases as control variables is determined. That is to say, optimization algorithms are applied to decide about some controllable variables while simulation methods evaluate the system response for each combination of controllable variables. Therefore, short-term reservoir operation optimization under flooding conditions can be formulated as a combination of a simulation model, which simulates system hydraulics for known flood hydrographs and operation policies, and a systematic search method which improves reservoir operations by optimizing release schedules or parameters of an operation policy so as to minimize flood damages. Since the governing equations need not to be represented in algebraic, continuous and differentiable functions, this approach circumvents unnecessary simplifications. Hence, modeling limitations are only associated with the simulation model (Unver & Mays 1990).

MODEL FORMULATION

The problem of optimal operation of river–reservoir systems deals with minimization of flood damages under constraints such as hydraulic physical rules and operational constraints on reservoir releases and water elevations at specified control points. The main components of an optimization model tackling this problem are the objective function and a set of constraints of the model, as will be described.

Objective function

The objective function is minimization of total flood damage, which is a function of discharges or depths in areas where damage occurs:

$$\min \mathrm{FD}\left(\sum_{i=1}^{n_\mathrm{d}} (Q_p)_i\right) \tag{1a}$$

$$\min \mathrm{FD}\left(\sum_{i=1}^{n_\mathrm{d}} (y_p)_i\right) \tag{1b}$$

where FD stands for flood damage; $(Q_p)_i$ and $(y_p)_i$ are respectively the discharge and depth at damage point i and n_d is the number of damage points (areas).

Constraints

Model constraints are designated in two categories: hydraulic and operational. Hydraulic constraints, defined as hydrologic/hydraulic equations considered in flow routing models, represent flow in the system. Hydrologic routing constraints are defined in the form of a continuity equation and a relation between storage volume and discharge in a reservoir or a river reach. Hydraulic routing constraints are full dynamic one-dimensional equations of unsteady gradually varied flow (Saint-Venant equations), including continuity and momentum equations in all computational reaches, equations representing initial conditions and finally upstream/downstream and internal boundary conditions. The mathematical formulation of hydraulic constraints may be written as:

$$f_{\mathrm{routing}}(I_t, R_t, y_{x,t}, Q_{x,t}, \partial Q_{x,t}/\partial x, \partial Q_{x,t}/\partial t, \ldots) = 0 \quad (2)$$

where I_t, R_t, $y_{x,t}$ and $Q_{x,t}$ are respectively inflow to the reservoir and release from it, flow depth and flow discharge. These variables and their partial derivatives with respect to space x and time t are interrelated through a nonlinear function f. The hydraulic constraints do not need to be expressed explicitly in the optimization formulation because they are embedded and used in the simulation model, implicitly.

The reservoir continuity equation is also considered as a hydraulic constraint which is a relationship between inflow to the reservoir, releases from it and the resulting change in its storage volume, which can be expressed as follows:

$$S_{t+1} = S_t + \Delta t(I_t - R_t) \quad (3)$$

where I_t and R_t are already defined, and S_t and S_{t+1} are two successive values of reservoir storage volume.

Operational constraints are inequalities describing ranges of variables, operational purposes, structural limitations, capacities and so on. Besides, choices of operators to control or bound some variable values are considered as operational constraints. These constraints include variations between minimum and maximum allowable discharges at specific points, physical or operational constraints controlling gate operations, and other constraints such as operation rules and target reservoir storages. Upper and lower bounds on variables and their maximum rate of change may be written as follows:

$$R_{\min} \le R_t \le R_{\max}, \quad |R_{t+1} - R_t| \le \Delta R, \quad S_{\min} \le S_t \le S_{\max} \quad (4)$$

where R_t and S_t are already defined, and $S_{\min}$ and $S_{\max}$ are respectively minimum and maximum values for reservoir storage volume. Also $R_{\min}$ and $R_{\max}$ are reservoir minimum and maximum values for reservoir release, respectively, and ΔR is the maximum allowable difference between releases of two successive time steps. ΔR value is chosen according to efficiency of outlet structures such as gated spillways or bottom outlets. It may also provide operators with the possibility of having control on release fluctuations. This is important in situations where sudden opening or closing of gates is not desirable. The minimum release constraint may be defined to consider instream flow requirements for water quality considerations.

SOLUTION PROCEDURE

Figure 1 shows data exchange between simulation and optimization modules. First, the optimization model generates randomly a set of decision variables (reservoir releases) which are used in the simulation model, where flow discharges and depths at control damage points are calculated by solving hydraulic or hydrologic routing equations. The objective function of the optimization

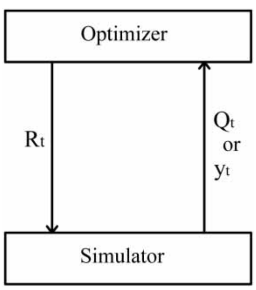

Figure 1 | Exchanging data between simulation and optimization models (Ahmed 2006).

model can be evaluated based on what is calculated by the routing model. Then another set of decision variables is generated through evolutionary equations of the PSO. This procedure is repeated until one of the predefined termination criteria are met, which are: (1) a certain predefined iteration number and (2) values from the best objective function stop improving over some iterations.

Simulation model

The simulation model performs flow routing in the river by either hydrologic or hydraulic routing models each having their own advantages and applications. Hydrologic methods are generally simple and fast. However, they may not be enough in some specific situations. For instance, backwater flow conditions occur when a flood passes a river tributary where a precise estimation of flow movement cannot be obtained by hydrologic routing methods. River–reservoir systems may fall into backwater conditions owing to tributaries, typhoons and tidal waves. Furthermore, hydrologic flow routing methods may not be as accurate as hydraulic methods, because they omit important effects of the full dynamic equations and can compute discharge hydrographs only at a specified number of control points approximately as opposed to a detailed water surface profile for dynamic routing.

Distributed hydraulic flow routing may be used because of the ability to compute flow discharge and depth variations in time and space, as precise estimation of damage due to a flood can depend on both temporal and spatial distributions of flow discharge and depth. The focus of the current study is on using hydraulic flow routing techniques along with a metaheuristic optimization algorithm. However, hydrologic routing methods are also considered for verification and comparison purposes. A brief explanation of flow routing models is given below.

Hydrologic routing

The Muskingum method, as one of the most applicable methods of hydrologic routing can be used to compute outflow hydrograph at a downstream control point of a river by knowing the upstream inflow hydrograph as follows:

$$Q_{t+1}^{\text{out}} = C_{1,\text{Musk}} Q_{t+1}^{\text{in}} + C_{2,\text{Musk}} Q_t^{\text{in}} + C_{3,\text{Musk}} Q_t^{\text{out}} \tag{5}$$

$$C_{1,\text{Musk}} = \frac{\Delta t - 2K_{\text{Musk}} X_{\text{Musk}}}{2K_{\text{Musk}}(1 - X_{\text{Musk}}) + \Delta t},$$

$$C_{2,\text{Musk}} = \frac{\Delta t + 2K_{\text{Musk}} X_{\text{Musk}}}{2K_{\text{Musk}}(1 - X_{\text{Musk}}) + \Delta t}, \tag{6}$$

$$C_{3,\text{Musk}} = \frac{2K_{\text{Musk}}(1 - X_{\text{Musk}}) - \Delta t}{2K_{\text{Musk}}(1 - X_{\text{Musk}}) + \Delta t}$$

where Q_t^{out} is outflow from routing model at downstream damage point, Q_t^{in} is inflow to routing model, Δt is computational time step and X_{Musk} and K_{Musk} are Muskingum model parameters. The Muskingum-Cunge method where geometric and hydraulic data are available can be used to estimate the parameters as follows (USACE 1994):

$$X_{\text{Musk-Cunge}} = \frac{1}{2}\left(1 - \frac{Q_0^{\text{in}}}{\bar{T} S_0 m v_0 L}\right),\ K_{\text{Musk-Cunge}} = \frac{L}{m v_0} \tag{7}$$

where Q_0^{in} is reference flow which is average inflow value (midway between the base flow and the peak flow), v_0 is initial velocity of flow, S_0 is river bed slope, $\bar{T}$ is flow top width, L is river length and $m$is wave celerity coefficient which depends on geometry of section ($m = 1.33$ for a triangular section and $m = 1.67$ for a wide rectangular section).

Hydraulic routing

Hydraulic routing methods are based on solving equations of unsteady flow in open channels. The principle equations are continuity and momentum equations known as Saint-Venant equations as follows:

$$\bar{T}\frac{\partial y}{\partial t} + \frac{\partial Q}{\partial x} = q_{\text{lat}} \tag{8}$$

$$\frac{\partial Q}{\partial t} + \frac{\partial (Q^2/A)}{\partial x} + gA\frac{\partial y}{\partial x} = gA(S_0 - S_f) \tag{9}$$

where x is longitudinal distance in channel direction, A is flow area, Q is flow discharge, q_{lat} is lateral discharge in unit width of channel, y is flow depth, g is gravity acceleration, S_0 is channel bed slope and S_f is friction slope which is obtained using the Manning equation $S_f = Q|Q|n_{\mathrm{man}}^2/A^2R_h^{4/3}$ in which n_{man} is the Manning roughness coefficient and R_h is hydraulic radius.

The Preissmann method (Cunge *et al.* 1980), as an implicit finite difference scheme, is used in this study in order to solve the equations. In this method, the continuity and momentum equations can be rewritten as follows (Cunge *et al.* 1980):

$$a_1 y_i^{n+1} + b_1 Q_i^{n+1} + c_1 y_{i+1}^{n+1} + d_1 Q_{i+1}^{n+1} = e_1 \tag{10}$$

$$a_2 y_i^{n+1} + b_2 Q_i^{n+1} + c_2 y_{i+1}^{n+1} + d_2 Q_{i+1}^{n+1} = e_2 \tag{11}$$

where i and n are space and time indices of computational nodes. The coefficients of the above equations, not presented, can easily be determined based on discretized forms of continuity and momentum equations in terms of known parameters (Cunge *et al.* 1980).

The equations, written for each adjacent pair of n computational points, together with two boundary conditions at two initial and end points of the reach constitute a penta-diagonal regular system of equations that can be solved using a three-diagonal approach.

Optimization model

Optimization algorithms fall into two general categories; gradient-based (i.e. classic mathematical) and gradient-free techniques. The latter methods are applicable to any simulation problem without the need for all functions and equations to be algebraic. Since the structure of the model in the present paper is the integration of a flow simulation model with an optimization algorithm, the proper and applicable optimization technique can be a gradient-free evolutionary search algorithm. Particle swarm optimization (Eberhart *et al.* 1996), as a meta-heuristic population based global optimization technique, is used in this study.

The PSO is similar to other evolutionary computation techniques in that a population of potential solutions to the problem under consideration is used to probe the search space. However, in the PSO, each individual of the population has an adaptable velocity (position change), according to which it moves in the search space. Moreover, each individual has a memory, remembering the best position of the search space it has ever visited (Eberhart *et al.* 1996). Thus, its movement is an aggregated acceleration toward its best previously visited position and toward the best individual of a topological neighborhood (Parsopoulos & Vrahatis 2002).

If the search space is D-dimensional, the location and velocity (position change) of particle i can be defined by D-dimensional vectors $X_{i,\mathrm{PSO}} = (x_{i1,\mathrm{PSO}}, x_{i2,\mathrm{PSO}}, \ldots, x_{iD,\mathrm{PSO}})^{\mathrm{T}}$ and $V_{i,\mathrm{PSO}} = (v_{i1,\mathrm{PSO}}, v_{i2,\mathrm{PSO}}, \ldots, v_{iD,\mathrm{PSO}})^{\mathrm{T}}$, respectively. The best location of particle i is defined as *P-best* vector ($P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})^{\mathrm{T}}$). Considering g as the index of the best particle ever found, i.e. the best solution among *P-best* vectors, and considering subscripts as iteration numbers, the following equations would determine where particles move to:

$$\begin{aligned} v_{id,\mathrm{PSO}}^{\mathrm{niter}+1} = {} & \chi \cdot [\omega \cdot v_{id,\mathrm{PSO}}^{\mathrm{niter}} + c_{1,\mathrm{PSO}} \cdot r_1^{\mathrm{niter}} \cdot (p_{id}^{\mathrm{niter}} - x_{id,\mathrm{PSO}}^{\mathrm{niter}}) \\ & + c_{2,\mathrm{PSO}} \cdot r_2^{\mathrm{niter}} \cdot (p_{gd}^{\mathrm{niter}} - x_{id,\mathrm{PSO}}^{\mathrm{niter}})] \end{aligned} \tag{12}$$

$$x_{id,\mathrm{PSO}}^{\mathrm{niter}+1} = x_{id,\mathrm{PSO}}^{\mathrm{niter}} + v_{id,\mathrm{PSO}}^{\mathrm{niter}+1} \tag{13}$$

where d is an integer number between 1 and D, i is particle index varying between 1 and N (N is swarm size), ω is inertia weight, $c_{1,\mathrm{PSO}}$ and $c_{2,\mathrm{PSO}}$ are positive constants termed respectively cognitive and social parameters, χ is a constriction factor to limit particle velocities, r_1 and r_2 are random numbers with uniform distribution in [0, 1] and niter is iteration number between 1 and a maximum iteration number at which the search terminates.

The PSO has proven to be a fast converging algorithm compared to other global optimization techniques like genetic algorithms (Parsopoulos & Vrahatis 2002). It has been applied successfully in a number of water resources applications such as basin-scale optimal water allocation (Shourian *et al.* 2008a, b; Mousavi & Shourian 2010a), optimal hydropower systems design and operation (Mousavi & Shourian 2010b), multiobjective reservoir operation (Baltar & Fontane 2008), storm water network design (Afshar 2008) and optimal design of cascade stilling basins (Bakhtyar & Barry 2008).

Existence of local optima could adversely affect the quality of PSO solutions. The 'function stretching technique' (Parsopoulos & Vrahatis 2002) has been used in this study to assist the PSO algorithm avoid local optima. The idea behind function stretching is to perform a two-stage transformation of the original objective function $F(x_{PSO})$. This can be applied immediately after a local minimum $\bar{x}_{PSO}$ of the function $F(x_{PSO})$ has been detected. This transformation is defined as follows:

$$G(x_{PSO}) = F(x_{PSO}) + \gamma_1 ||x_{PSO} - \bar{x}_{PSO}|| (\mathrm{sgn}(F(x_{PSO}) - F(\bar{x}_{PSO})) + 1) \quad (14)$$

$$H(x_{PSO}) = G(x_{PSO}) + \gamma_2 \frac{\mathrm{sgn}\,(F(x_{PSO}) - F(\bar{x}_{PSO})) + 1}{\tanh\,(\mu(G(x_{PSO}) - G(\bar{x}_{PSO})))} \quad (15)$$

where γ_1, γ_2 and μ are arbitrary chosen positive constants. A set of values $\gamma_1 = 5{,}000$, $\gamma_2 = 0.5$ and $\mu = 10^{-10}$ could be appropriate (Parsopoulos & Vrahatis 2002). Sgn(·) defines the well-known triple valued sign function.

The first transformation stage, defined in Equation (14), stretches the objective function $F(x_{PSO})$ upwards and eliminates all the local minima with values higher than the value of the obtained minimizer that are located above $F(x_{PSO})$. In the second stage, Equation (15), the detected minimum is changed to a maximum and the neighborhood of $\bar{x}_{PSO}$ is stretched upwards, since it assigns higher function values to those points. Both stages do not alter the local minima located below $\bar{x}_{PSO}$; thus, the location of the global minimum is left unaltered. The parameter γ_1 controls the upward stretching of the objective function, performed by $G(x_{PSO})$. Due to this transformation, the local minima with function values higher than the one found are eliminated. In practice, high values of γ_1 are used in multidimensional problems to ensure that the local minima with function values higher than the one detected, will be eliminated. The parameters γ_2 and μ determine the range of the effect and the magnitude of the elevation, respectively. A larger area around the local minimizer is affected by increasing the γ_2 parameter (Konstantinos *et al.* 2004).

This study takes the PSO algorithm linked to flow routing models and uses it in solving short-term optimal operation of single river–reservoir systems. Note that although applications in the present study are for single reservoir systems, they are under a greater computation burden due to their linkage to a hydraulic flow routing model compared to a multireservoir PSO application not linked to such a routing model.

APPLICATIONS

Two application problems of optimal reservoir operation under flooding conditions were studied. The first application was about solving the benchmark problem of Bishop Dam defined in the HEC-5 manual (USACE 1998) through which the optimization–simulation model results are compared with those of the HEC-5 model. The second application was related to a real case study in which the significance of the PSO-Venant model was evaluated.

Optimizing operation of Bishop reservoir

The objective in this problem was minimizing peak discharge at Zelma control point on Rocky river downstream the Bishop Dam (USA) due to a known flood hydrograph entering the dam (USACE 1998). Figure 2 shows a schematic representation of the dam reservoir and its downstream control point. Flood data during 20–28 December 1964, comprising reservoir inflow and inter-basin flow hydrographs with base time of 213 hours and 3-hour time steps were used (Figure 3; USACE 1998). In HEC-5, reservoir storage capacity is divided into a number of zones including inactive, buffer, conservation, flood and surcharge zones with the elevations presented in Table 1 for this example.

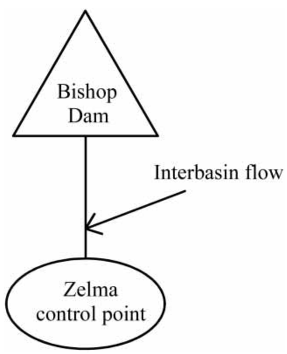

Figure 2 | Reservoir and its downstream control point; Bishop Dam problem (USACE 1998).

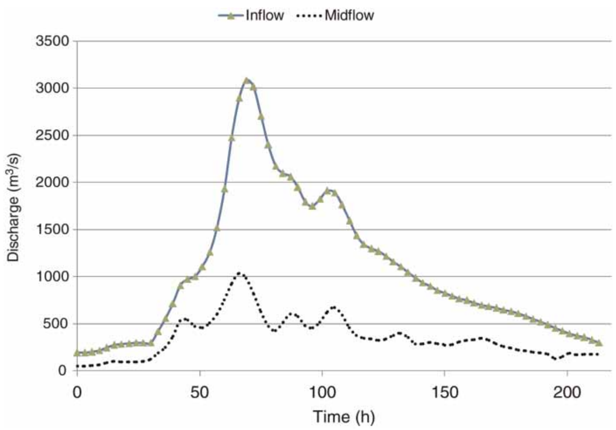

Figure 3 | Reservoir inflow and inter-basin flow hydrographs; Bishop Dam problem (USACE 1998).

Table 1 | Bishop reservoir storage levels, volumes and elevations (USACE 1998)

Level number	Storage level, top of	Elevation (m)	Cumulative storage (1,000 m^3)
1	Inactive pool	250.2	131,438
2	Buffer pool	250.4	134,000
3	Conservation	251.5	146,480
4	Flood control	283.2	562,248
5	Dam	286.8	630,063

Maximum allowable release based on outlet structures' capacity is also shown in Figure 4. Initial, minimum and maximum reservoir storage volumes were considered to be 146.48, 131.438 and 575 million cubic meters (MCM),

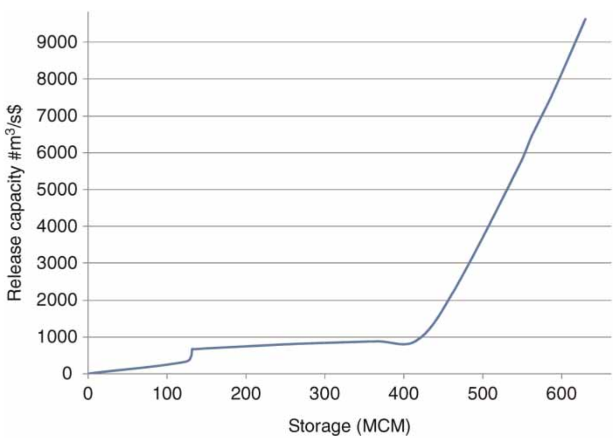

Figure 4 | Outflow capacity curve of Bishop Dam (USACE 1998); MCM: million cubic meters.

respectively. The minimum desired and minimum required flows were equal to 80 and 3 m^3/s, respectively. Releases were made equal to or greater than the desired minimum flow when the reservoir storage is greater than the top of buffer storage, while they were made equal to the minimum required flow if reservoir storage falls into the buffer zone (USACE 1998). Maximum rate of change in reservoir outflow per hour was set as 70 m^3/s for increasing discharges, and 225 m^3/s for decreasing ones (USACE 1998).

Four models were examined; the first was the well--known HEC-5 simulation model, and others were optimization–simulation models where PSO is linked to Muskingum (PSO-Muskingum), Muskingum-Cunge (PSO-MuskCunge) and Saint-Venant-based (PSO-Venant) routing models. The PSO decision variables were reservoir releases with 72 unknowns.

HEC-5 introduces a number of methods for modeling flood operation of which gate regulation curves (GRCs) is an efficient method in decreasing peak discharge at a downstream control point (USACE 1998).

Initial conditions and Muskingum parameter values in the PSO-Muskingum model were identical to those used in HEC-5 model, i.e. $X_{\mathrm{Musk}} = 0.3$ and $K_{\mathrm{Musk}} = 3$ hours. In the Muskingum-Cunge method, the damage control point was considered to be at 10 km from the dam and the longitudinal slope of the river reach was assumed to be 0.001. The Manning coefficient was taken as 0.03 with a 40-m width rectangular cross-section. These values were selected so that $X_{\mathrm{Musk-Cunge}}$ and $K_{\mathrm{Musk-Cunge}}$ became almost equal to those used in the PSO-Muskingum model. In the PSO-Venant model, river data, including cross-sectional geometry and bed slope, were assumed to be constant and identical to those used in the PSO-MuskCunge model. The PSO parameters found by a trial and error procedure were chosen as $N = 100$, $\chi = 0.9$, $c_{1,\mathrm{PSO}} = 2.5$, $c_{2,\mathrm{PSO}} = 1.5$ and $0.1 \leq \omega \leq 1.2$.

The peak discharge at Zelma control point, as the objective function of the optimization models, calculated from HEC-5 (with GRC method), PSO-Muskingum, PSO-Musk-Cunge and PSO-Venant were respectively 1,563, 1,275, 1,282 and 1,277 m^3/s, reflecting a 18% decrease for the optimization–simulation model results compared to the GRC method. The time variation of reservoir storage and flood hydrographs at reservoir and control points results from different models are compared in Figures 5–7. When the inflow flood hydrograph enters the reservoir, the release rate will increase gradually in order to prevent any sudden change in storage volume (Figure 5). Initially the release and inflow rates were almost the same. Then inflow rate exceeded release rate, causing storage increase up to maximum value, and the reservoir stays at its maximum level for a while before reservoir draw down (Figures 5 and 7).

It is noteworthy that the Bishop Dam problem has been considered for verifying whether the PSO-Venant model, before it is used in a more complicated problem, is able to arrive at a solution comparable to those obtained by hydrologic routing-based methods in a problem where hydrologic routing techniques were adequate. Besides, comparison of the results of the optimization–simulation models with those of HEC-5 has demonstrated the significance of optimizing release schedules regardless of what flow routing method is used.

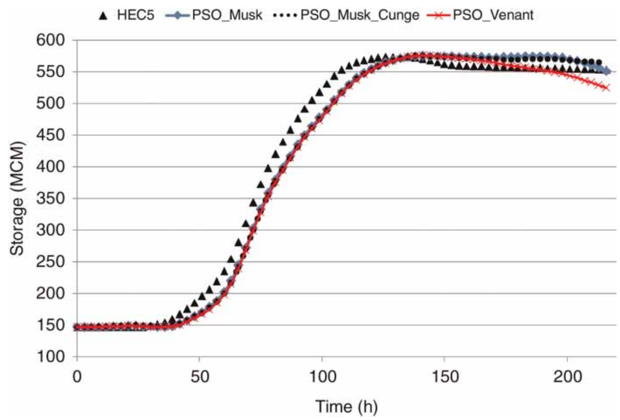

Figure 7 | Comparison of HEC-5 and other optimization models results with respect to reservoir storage volume in Bishop Dam problem.

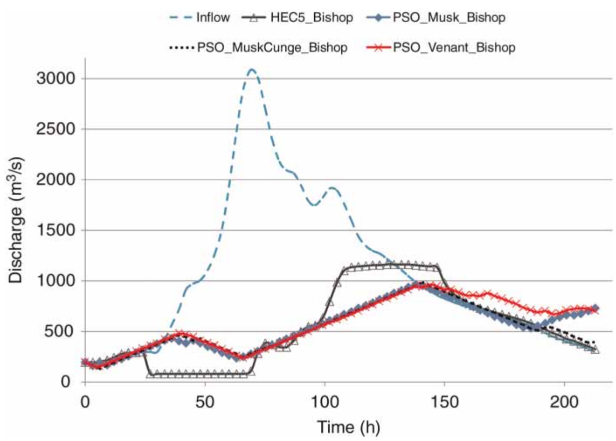

Figure 5 | Comparison of HEC-5 and other optimization models results with respect to reservoir releases in Bishop Dam problem.

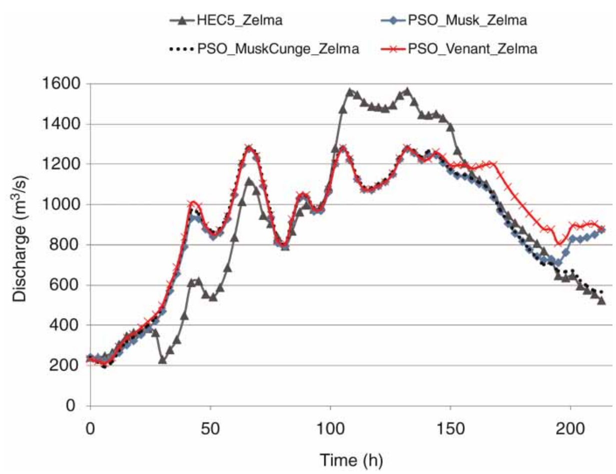

Figure 6 | Comparison of HEC-5 and other optimization models results with respect to discharge hydrograph at Zelma control point in Bishop Dam problem.

Optimizing operation of Upper Gotvand reservoir

In the foregoing, the models were tested through a benchmark problem. Herein, optimization of Upper Gotvand (UG) reservoir operation was considered as a real problem. The problem is part of a dam break study project on the Dez and Karun river–reservoir systems as the most important surface water resources in Iran. It is intended to study the damaging effects of dam break, and the resulting floods on downstream areas with urban, agricultural and industrial land uses, in order to develop an emergency action plan (EAP). The project incorporates various disciplines – hydraulics and flood routing, hydrology and flood forecasting, socioeconomics, databases and GIS.

The UG dam (height 180 m) is under construction on Karun river, the largest river in Iran (800-km long), originating from the Zagros mountains and flowing northeast to southwest towards the Persian Gulf. The dam site is located in Khuzestan province in southwest Iran, 30 km from Shushtar city and 12 km from Gotvand city. The average historical long-term annual water yield of Karun river at the dam location is 454 m^3/s with a basin area as large as 32,525 km^2. Figure 8 presents a schematic representation

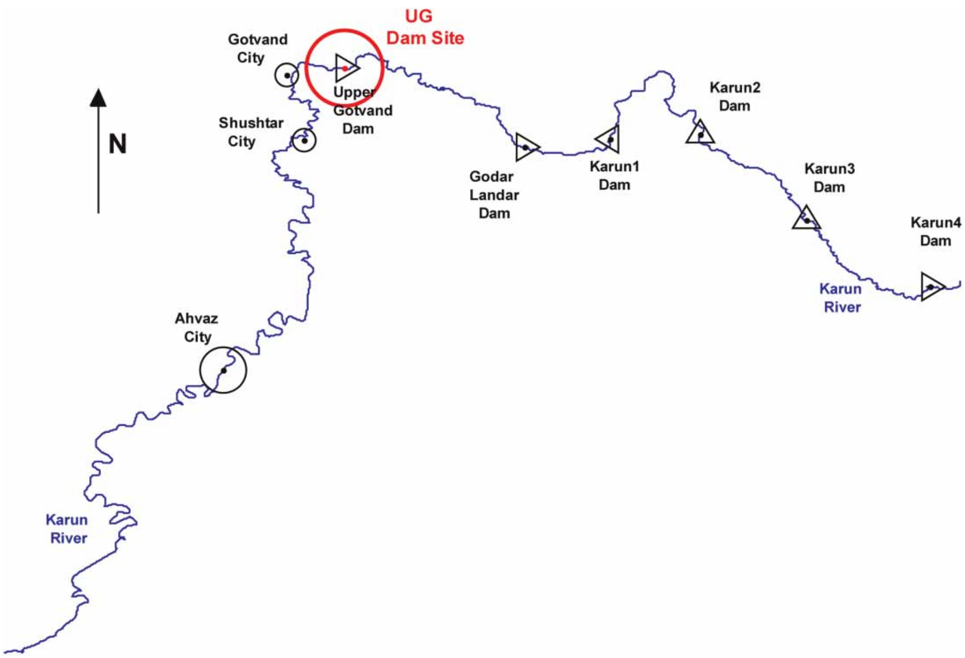

Figure 8 | Schematic representation of Karun river–reservoir system.

of the Karun river–reservoir system. The UG is a multipurpose dam designed for flood control, hydropower generation and water supply. Being the last reservoir of the Karun cascade dams with the largest storage capacity, the UG reservoir can play a crucial role in controlling seasonal floods originating from upstream sub-basins. Therefore, development of a framework for determining an optimal release schedule for the UG reservoir, which minimizes downstream flood damages given a known inflow flood hydrograph, is studied in this paper.

Initial storage volume was considered equal to 4,097 MCM, and minimum and maximum storage volumes are 1,290 and 5,177 MCM, respectively. The objective function of the PSO-Venant model is minimization of flood damage in downstream areas of the UG dam. Flood damage is a function of maximum flow depth at points where damage occurs downstream of the reservoir depending on land use data as follows:

$$\min \sum_{i=1}^{n_\mathrm{d}} \mathrm{FD}(\mathrm{LU}, (y_p)_i) \tag{16}$$

where FD is flood damage function, LU is land use type, $(y_p)_i$ is maximum depth at ith damage point and n_d is number of damage control points. The estimated damage function based on economic studies of the project is shown in Figure 9 (Water Research Institute 2010). This function was defined in terms of three significant land use types based on available data including buildings, roads and cultivation at damage areas downstream the UG dam. The basis for FD estimation was the information available on economic values of different types of lands (per m^2) for the region under study. So FD value at each damage point is calculated based on its land use type and peak flood

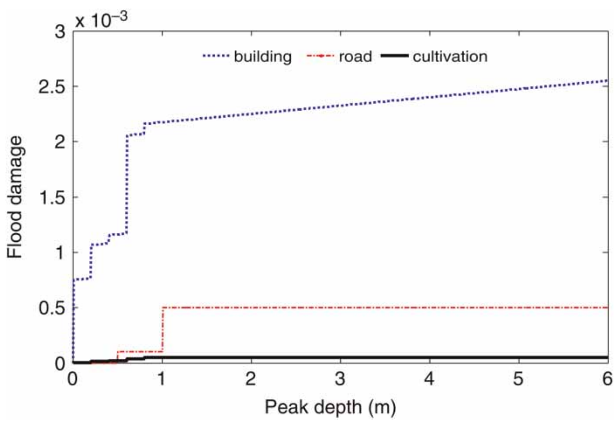

Figure 9 | Flood damage function for different types of land use data (Water Research Institute 2010).

depth. The total flood damage is estimated by summation of calculated FDs at all damage points. Estimation of the total flood damage requires computing flow depth at different damage points for all time steps during floods, a requirement that cannot be met by hydrologic routing methods. This makes use of a PSO-Venant model with a hydraulic routing method inevitable.

It is noteworthy that the objective of the problem under study was to use a simulation model of hydraulic river routing embedded into a PSO algorithm as an optimization model to minimize total flood damage which is a function of peak depths at inundated areas. In order to compute peak depths at damage areas, a one-dimensional (1-D) flow routing model has been developed and used to solve Saint-Venant equations and the flow depth at each point of inundated area has been calculated from the difference between the water surface elevation at the nearest node of river and the elevation of that point of inundated area. This approximation could provide a reasonable estimation of flood damage at inundated areas. Of course a 2-D hydraulic routing model could have provided more accurate results, but it is not possible to use such a model because of the computational burden.

The system consists of the UG dam reservoir and Karun river reach downstream the reservoir with a length of 390 km and 363 lateral cross sections obtained from hydrographic surveying. The 1,000-year flood hydrograph with a 9-day base time (Figure 10) estimated by flood frequency analysis (Water Research Institute 2010) has been considered as the inflow hydrograph to the reservoir. Hydrological studies have shown that there are no significant inter-basin flows from tributaries into Karun river (Water Research Institute 2010).

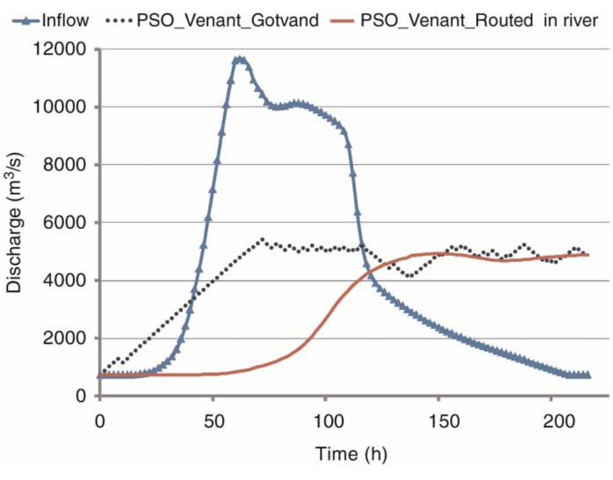

Figure 10 | 1,000-year inflow flood hydrograph compared to optimal reservoir release hydrograph at UG dam and routed hydrograph through river reach; PSO-Venant model.

The main parameter calibrated in hydraulic flow routing model in the second case study was the Manning roughness coefficient (n_{man}). In order to calibrate this parameter, the whole river reach was divided into a number of subreaches and n_{man} parameter was calibrated for each subreach by changing its value so that a good match was reached between observed and simulated depths (discharges). The results showed that the values of n_{man} varied between 0.026 and 0.034 with an average value of about 0.03 (Water Research Institute 2010). On the other hand, the simulation results showed that the larger depths, which are more important to total flood damage, are less affected by those calibration parameters and the match between observed and simulated discharges remained acceptable if a constant Manning coefficient is used. The average n_{man} equal to 0.03 was therefore used. Moreover, the parameters of Preissmann method i.e. α, Δx and Δt, were respectively selected as 0.8, 500 m and 100 seconds, based on a trial and error procedure in such a way that a stable and convergent solution was achieved.

The decision variables of PSO-Venant model were reservoir releases at 109 time steps according to 109 two-hour time steps of Upper Gotvand project, while flow depths at damage points are state variables that were computed by hydraulic routing model. Each routing model or fitness evaluation lapses about 31 seconds (using a personal computer – 3 GHz CPU speed). Therefore, the total run time for the model with 100 PSO particles and 100 iterations was about 86 hours. Note that, such a model cannot be used for online or real-time decision making during floods, but rather for building flood control rule curves.

The results of the PSO-Venant model are shown in Figures 10–15. Figure 10 shows the inflow flood hydrograph compared to the release hydrograph at the UG dam site and the routed hydrograph through the most downstream point of the river. Considerable peak attenuation is seen in the routed flood hydrograph. Figure 11 presents variation of reservoir storage volume.

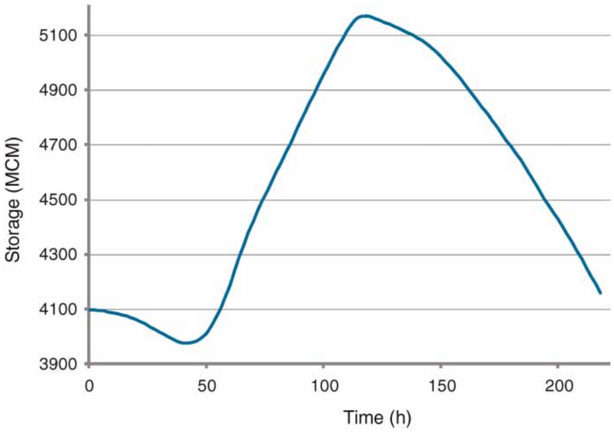

Figure 11 | Storage volume variations of UG reservoir; PSO-Venant model; MCM: million cubic meters.

As soon as the incoming flood discharge begins to increase, reservoir release will also increase to provide additional storage so that as the peak flood discharge arrives, the release will not need to be as large. This advantage of a multiperiod optimization is, however, based on the assumption of having perfect foresight of the inflow hydrograph. After the peak discharge was over and inflow rate began to decrease (at hour 62), the release rate was balanced so as to deplete flood control volume of the reservoir. Figure 12 shows the variation of the best objective function value versus PSO iteration number.

The longitudinal profile of water surface associated with the best solution alongside the river bed elevation in the selected river reach is presented in Figure 13. Figures 14 and 15 respectively show the 111th and 121st river cross sections at km 93 and 103 of the river reach (between Shustar

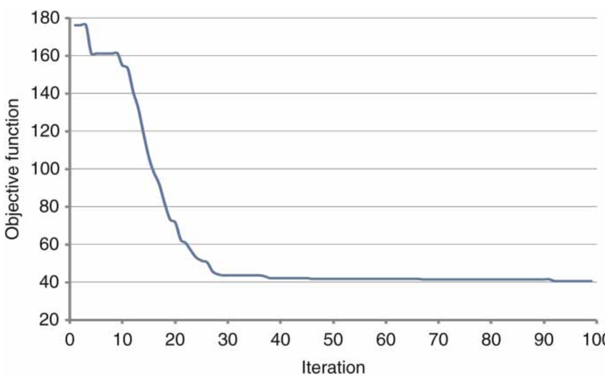

Figure 12 | Objective function values of the g-best solution at different iterations of PSO-Venant model.

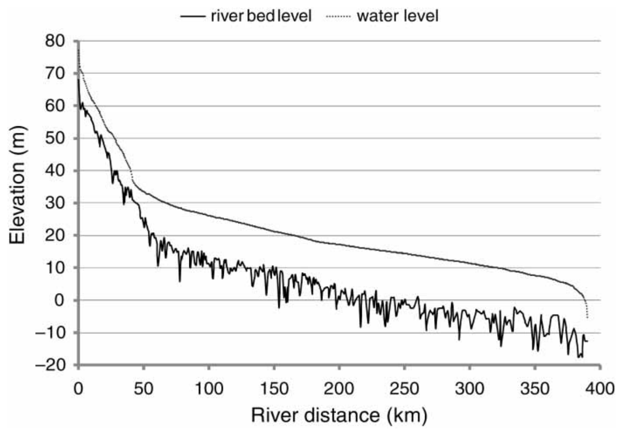

Figure 13 | Longitudinal profile of water level in selected river reach based on best values of reservoir releases.

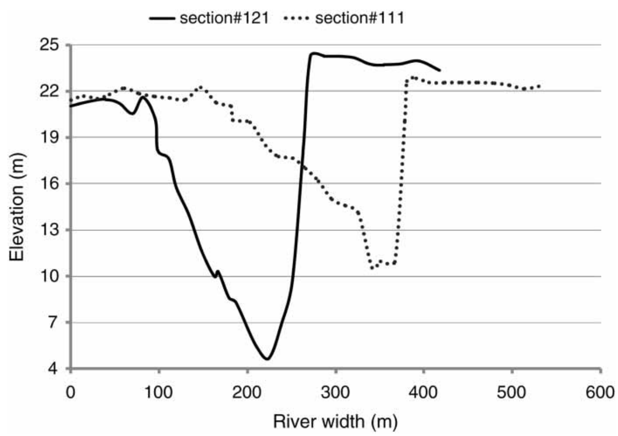

Figure 14 | Sample cross sections downstream UG dam.

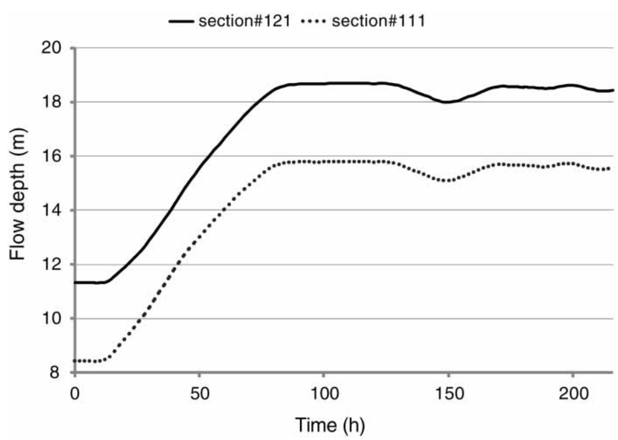

Figure 15 | Flow depth variations during flood period at sample cross sections resulting from the PSO-Venant model.

and Ahvaz cities) and their related flow depth variations with the greatest values of downstream flood damages. Land use maps reveal that the most vulnerable area with a dense cultivated land is located between Shushtar (km 36) and Ahvaz (km 186) cities. This fact was sensed by the model trying to reduce flood peak depth in this area as much as possible. Therefore, the PSO-Venant model and its hydraulic routing module are capable of accounting for a spatial flood damage function, a feature that cannot be considered by hydrologic routing models.

We are also keen to know what will happen if a hydrologic routing method is used instead of hydraulic routing when cross-section information is available. However, we need to build a basis to make it possible to compare the hydrologic and hydraulic routing methods in such a situation. Therefore, some simplifications regarding river geometric parameters are required to enable such a comparison. So, the river was assumed to be prismatic with a 100-m wide rectangular cross section, a 390-km length, an average slope of 0.0002 and Manning coefficient of 0.03.

Note that the assumptions made, although unrealistic, should be viewed from the view point of what they have been used for. In this regard, it is important to say that the result of the comparison will only give an idea about the significance of the possible differences between the methods, which is the main point of making the comparison.

The optimal reservoir release hydrograph of the model was taken as an inflow hydrograph to the downstream river reach. The PSO-Venant model was applied and the resulted outflow hydrograph at the river end was used in computing Muskingum parameter values, X_{Musk} and K_{Musk}, which were obtained as equal to 0.355 and 98,533 seconds, respectively; then the Muskingum model was used in every two adjacent nodes (with a 500-m distance) of the selected river reach and the flood hydrograph at every node was determined. The Manning equation was subsequently used to compute flow depth and the resulting flood damage at every node. Figure 16 compares the cumulated flood damages around some critical nodes of the river computed from the above mentioned procedure and hydraulic routing. Total values of flood damages computed from hydrologic and hydraulic routing methods are respectively equal to 2,565 and 3,030 suggesting that hydrologic routing could be significantly erroneous in this problem.

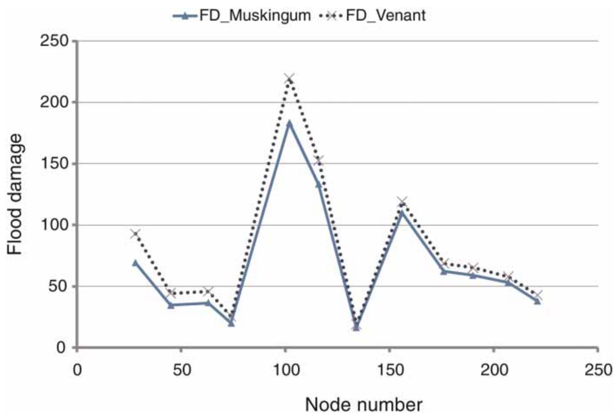

Figure 16 | Cumulated flood damage around 20 critical nodes of river.

SUMMARY AND CONCLUSIONS

Optimization–simulation models for optimizing real-time reservoir systems operations under flooding conditions were developed in this study by integrating PSO algorithm and simulation models including both hydrologic (Muskingum and Muskingum-Cunge) and hydraulic flow routing models. The developed models were tested first to determine optimal operation of Bishop Dam reservoir as a benchmark example problem in HEC-5. The model results were analyzed and compared with those of the GRC method provided in the HEC-5 manual. As expected and since no optimization algorithm is used in the GRC method, all the optimization models outperformed the GRC with about 18% decrease in peak discharge at the control point. This of course was done as a verification step for the models developed and not to exactly focus on the percentage of improvement achieved by the models.

The PSO-Venant model was then used in flood damage reduction studies of the UG dam system as a real case study in Iran. In this case, spatial variation of flood damage due to significant land use change downstream from the dam site justifies application of hydraulic flow routing for flood damage estimation. The associated optimization–simulation problem is, in fact, highly nonlinear and difficult-to-solve with partial differentian equations as non-algebraic functions in its simulation part cannot be solved via traditional gradient-based optimization techniques. Extensive data regarding river geometry and bed slope were gathered. Then optimal reservoir releases against a 1,000-year inflow flood hydrograph were determined. The results showed how the model through its hydraulic routing module can sense the effect of land use change on damage estimation and how the results are adapted in response to spatial damage objective function of the model. A simple comparative analysis was also made to show that hydrologic routing models may not provide an accurate estimation of flood damage when enough data are available to build a spatial flood damage function.

It is noteworthy that the PSO-Venant model uses a spatial damage function evaluated through a 1-D distributed routing model, instead of a more accurate 2-D one. On one hand, a 2-D routing model provides with the possibility of accurate flood damage estimation, but impossibility of being used in an optimization model. On the other hand, hydrologic routing could be used with ease of application and efficiency when used in optimization models. The PSO-Venant model, with a 1-D distributed routing model linked to a metaheuristic optimization algorithm, is something in between those extremes. Which approach is better and how much detail the simulation or optimization module needs depend on the level of expertise with distributed hydraulic routing and optimization techniques; computational technology; data availability on river cross-sections, land uses and the properties located in the flood plain; and the objectives of the problem under study. The level of data availability in the case study was consistent with the modeling approach used, because there were relatively enough data on river cross-sections while the information available on the properties and their values was not complete.

There are some aspects that should be dealt with in future studies: (1) the optimization model used has perfect foresight of the inflow hydrograph, an issue which does not exist in reality. In this regard, a forecast-based approach in which forecasts on future inflows are made adaptively could be used if the model is to be applied in online and real-time reservoir operations and decision making during floods; (2) A serious difficulty when a time-consuming simulation model, such as a hydraulic routing model, is employed in an optimization–simulation approach is the high computational burden of the resulting model that limits its application in real-time decision-making problems. Parallel processing and metamodeling techniques could be used to deal with this difficulty. In metamodeling, the high-fidelity simulation model is approximated using a function approximation technique such as artificial neural networks, Bayesian regression and so on. Then the approximate model, metamodel, which has been trained offline or online (in course of optimization), will replace the time-consuming simulation model making the optimization–simulation model much faster to run. This is a possibility that could be considered when the proposed optimization–simulation model is to be extended to multi-reach multi-reservoir river–reservoir systems or 2-D hydraulic routing models are to be used.

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