Genetic Algorithm-Based Discharge Estimation at Sites Receiving Lateral Inflows

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Abstract: The genetic algorithm (GA) technique is applied to obtain optimal parameter values of the standard rating curve model (RCM) for predicting, in real time, event-based flow discharge hydrographs at sites receiving significant lateral inflows. The standard RCM uses the information of discharge and effective cross-sectional flow area at an upstream station and effective cross-sectional flow area wave travel time later at a downstream station to predict the flow rate at this last site. The GA technique obtains the optimal parameter values of the model, here defined as the GA-RCM model, by minimizing the mean absolute error objective function. The GA-RCM model was tested to predict hydrographs at three different stations, located on the Upper Tiber River in central Italy. The wave travel times characterizing the three selected river branches are, on the average, 4, 8, and 12 h. For each river reach, seven events were employed, four for the model parameters' calibration and three for model testing. The GA approach, employing 100 chromosomes in the initial gene pool, 75% crossover rate, 5% mutation rate, and 10,000 iterations, made the GA-RCM model successfully simulate the hydrographs observed at each downstream section closely capturing the trend, time to peak, and peak rates with, on the average, less than 5% error. The model performance was also tested against the standard RCM model, which uses, on the contrary to the GA-RCM model, different values for the model parameters and wave travel time for each event, thus, making the application of the standard RCM for real time discharge monitoring inhibited. The comparative results revealed that the RCM model improved its performance by using the GA technique in estimating parameters. The sensitivity analysis results revealed that at most two events would be sufficient for the GA-RCM model to obtain the optimal values of the model parameters. A lower peak hydrograph can also be employed in the calibration to predict a higher peak hydrograph. Similarly, a shorter travel time hydrograph can be used in GA to obtain optimal model parameters that can be used to simulate floods characterized by longer travel time. For its characteristics, the GA-RCM model is suitable for the monitoring of discharge in real time, at river sites where only water levels are observed.

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Introduction

Determination of flow discharge at a river site is required for water resources planning and management, and controlling floods. Discharge is obtained from the measurement of flow depth, channel width, and flow velocity. For these measurements, the river section is often equipped with hydrometric sensors for flow depth measurements, and cableway and current meter for velocity measurements and a topographic surveying is carried out for channel cross section. Compared to the velocity and channel cross-section measurements, flow depth measurement is fairly simple and relatively inexpensive.

Although the hydraulic modeling may be used for translating discharge into flow depth, it requires topographic information that neither exists nor is readily available for most of the river cross sections. Hence, researchers tend to employ simple approaches such as the Muskingum method, which relates the outflow and inflow hydrographs through parameters depending on the hydraulic and morphological properties of the channel (Franchini and Lamberti 1994). However, the estimation of these parameters becomes difficult when lateral inflow is predominant during the evolution of a flood (Moramarco et al. 2005).

Franchini et al. (1999) developed a methodology based on a variable parameter Muskingum-Cunge model with a specific parametrization scheme. However, the application of this model is complex, since it requires the estimation of nine parameters. Moramarco and Singh (2001), on the other hand, developed a simple and practical model that uses only the water levels and allows quick estimation of the flow conditions through the assessment of two parameters. However, both of these models are applicable for the cases where there is negligible lateral inflow contribution.

Moramarco et al. (2005) developed a physically based rating curve model (RCM), which can be applied to cases where lateral inflow is significant. The RCM assumes a linear relation between the upstream and downstream flow variables and it is especially useful when the downstream boundary condition is unknown or velocity measurements are available for low flows only. The RCM uses a physically based two-parameter linear formulation

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J. Hydrol. Eng., 2009, 14(5): 463-474

that relates flow rate at a downstream site to flow rate at an upstream site and flow areas at both sites. The values of model parameters are found using information of upstream and downstream base flow and peak discharge. The RCM finds the base flow either through the flow velocity measurements during low flows at the downstream gauging section or as the product of upstream mean velocity and downstream flow area. The model computes the downstream peak discharge as the contribution of the upstream discharge delayed for the wave travel time and the lateral inflows that are estimated by the continuity equation. The RCM model, for each event that occurs in the same river reach, has to determine the wave travel time and the model parameters. In other words, the model uses different values of model parameters and wave travel time for each event at each river reach.

Moramarco et al. (2005) tested the RCM model using different flood events that occurred in three different reaches of the Upper Tiber River basin in central Italy. The RCM model was also tested against the Muskingum (Moramarco et al. 2005) and the artificial neural network (ANN) (Tayfur et al. 2007) models. Moramarco et al. (2005) concluded that the RCM is more reliable than the Muskingum model if the rating curve is unknown at the downstream end and Tayfur et al. (2007), on the other hand, showed that the ANN outperforms the RCM. It should be noted however, that for the calibration of the RCM model, it is required that the rising limb of the stage hydrograph is observed until at least peak stage, and this makes its application for discharge monitoring in real time inhibited.

Although ANNs are very powerful interpolators, they lack the extrapolation capability. For example, Tayfur et al. (2007) investigated the extrapolation capability of ANN for predicting peak discharge outside of the range of values employed in network training. They showed that when an event whose peak discharge is 100 m^3/s is used in network training to predict an event whose peak discharge is 200 m^3/s, the peak discharge was underpredicted with a 50% error. As such, they cannot be applied to ungauged basins (Tayfur et al. 2007). As it is presented in a later section, the genetic algorithm (GA)-RCM model does not have such a shortcoming.

Furthermore, although ANNs can solve very complex nonlinear problems, they are black box models that do not reveal insight into understanding the physics of the processes. ANN inspired by the biological nervous system captures the behavior of a system through a training algorithm, which minimizes error function while finding optimal values for the connection weights. GA, on the other hand, finds optimal values of the existing model parameters through minimization of the error objective function. With regard to the methodologies and algorithms, both do not reveal insight into the understanding of the basic processes of the physical event. In that sense, both are black box methods. However, the ANN model has higher order black box model characteristics since it does not yield an empirical equation. GA, on the other hand, finds optimal values of existing empirical equations that can be readily used for predictive purposes. These existing empirical equations may shed a light onto the understanding of the physics of the processes.

GAs have recently found wide application in water resources engineering (Guan and Aral 1998; Sen and Oztopal 2001; Jain et al. 2004; Guan and Aral 2005; Singh and Datta 2006; Cheng et al. 2006; Aytek and Kisi 2008), flood forecasting (Liong et al. 1995; Wu and Chau 2006), and rainfall-runoff modeling (Cheng et al. 2002, 2005; Hejazi et al. 2008). Cheng et al. (2002) introduced a methodology that used GAs in conjunction with a fuzzy algorithm to automatically calibrate the parameters of the Xinanjiang rainfall-runoff watershed model with multiple objectives such as peak rate, time to peak, and total runoff volume. Cheng et al. (2005) developed another model, which combined GAs with a fuzzy algorithm to improve the quality and efficiency of a conceptual rainfall-runoff model in a cluster of computers. Their methodology was able to significantly reduce the overall optimization time and produce results compatible with observed data. Hejazi et al. (2008) employed multiobjective GAs to calibrate parameters of a storm-event distributed hydrologic model. They showed that the calibration procedure with user interference resulted in a better performance of the model and produced reasonable model parameters in terms of their values and spatial distribution.

Since the RCM model calibration is based on specific points alone (base flow and peak discharge), this study employs the GA technique to address a more robust calibration of parameters of the RCM model. The purpose of this study is not to present a new model, but to investigate if the performance of the RCM model can be enhanced through a calibration procedure based on the GA technique. This would make the new RCM model suitable for applications in a context of real-time discharge monitoring, at gauged river sites where only water levels are measured and the rating curve is unknown.

Genetic Algorithm

GAs are nonlinear search and optimization methods inspired by a biological process of natural selection and the survival of the fittest. They make relatively few assumptions and do not rely on any mathematical properties of the functions (such as differentiability and continuity) and this makes them more generally applicable and robust (Liong et al. 1995; Goldberg 1999).

Basic units of GA consist of "*bit*," "*gene*," "*chromosome*," and "*gene pool*." *Gene* represents a model parameter or a decision variable to be optimized. A *chromosome* is the combined set of all the genes. When there are more than one variable, then each variable is the gene and combination of genes forms the chromosome, each of which is a possible solution for the variables. When deciding the chromosomes of the variables, detailed information on the physical problem should be available. One should know which gene stands for which variable. Only the necessary variables should be considered since many variables might prevent the proper work of GA (Goldberg 1999; Sen 2004).

The main GA operations basically consist of "*generation of initial gene pool*," "*evaluation of fitness for each chromosome*," "*selection*," "*cross over*," and "*mutation*." An initial population of chromosomes can be randomly generated by, for example, a uniform distribution or a normal distribution (Sen 2004). It is beneficial to generate random numbers in the solution space, thus allowing the trial of many possibilities. The order of genes in a chromosome should be decided at the beginning and should not be changed during an operation (Sen 2004).

Each individual is tested empirically in an "environment" and is assigned a numerical evolution of its merit by a fitness function. Fitness of each chromosome is obtained in two steps. First, the value of each objective function for each chromosome is computed by substituting the chromosome (variables) into the function. Fitness of each chromosome is then obtained as (Sen 2004)

J. Hydrol. Eng., 2009, 14(5): 463-474

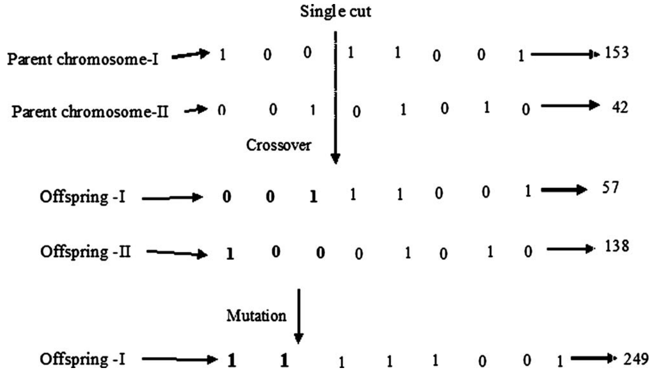

Fig. 1. Example for crossover and mutation operations

$$F(C_i) = \frac{f(C_i)}{\Sigma f(C_i)} \tag{1}$$

where C_i=chromosome i; $F(C_i)$=fitness value of chromosome that is the percentage of variable in the pool; and $f(C_i)$=value of objective function evaluated for chromosome i.

Selection can be performed randomly. Random selection, for example, can be based on a roulette wheel (Sen 2004) or ranking where the chromosomes are ranked according to their fitness from the fittest to the weakest and then the fittest ones are copied on the weakest ones.

To create the new generation, a combination process of two parent chromosomes is performed by *cross over*. The chromosomes from the current generation are selected for the recombination process. The crossover between the chromosomes is done by simply interchanging the selected genes. Fig. 1 is an example for a single cut crossover operation where the first two chromosomes are subjected to the crossover by the single cut from the third digit, yielding new chromosomes (offspring) at the bottom.

The last operation in GA is the *mutation* by which bits are reversed (i.e., *1 to 0* or *0 to 1*). It can be applied on one (or more) bit(s) of a chromosome. In the GA search method, this is the perturbation that allows the GA to seek out new and novel solutions to minimize the chance of getting trapped in a local minimum. By this process, the next trend would faster converge to solution or may diverge from the solution, although it is expected that the algorithm would do better with the mutation operation. In general, about 5% of the bits are subjected to mutation since the higher rate of perturbation might disrupt reaching the optimal solution. Fig. 1 is an example presenting that the value of 185 goes to 57 after crossover and then to 249 after mutation, scanning a large area of the solution domain. The details of GA can be obtained from Goldberg (1999) and Sen 2004, among others.

Rating Curve Method

The model developed by Moramarco et al. (2005), called the rating curve method (RCM), is briefly summarized. Discharge at the downstream station is related to measured flow variables at the upstream station as

$$Q_d(t) = \alpha \frac{A_d(t)}{A_u(t-T_L)} Q_u(t-T_L) + \beta \tag{2}$$

where Q_u=upstream discharge; Q_d=downstream discharge; A_d and A_u=effective downstream and upstream cross-sectional flow areas obtained from the observed stages, respectively; T_L=wave travel time depending on the wave celerity c; and α and β=model parameters (Moramarco et al. 2005).

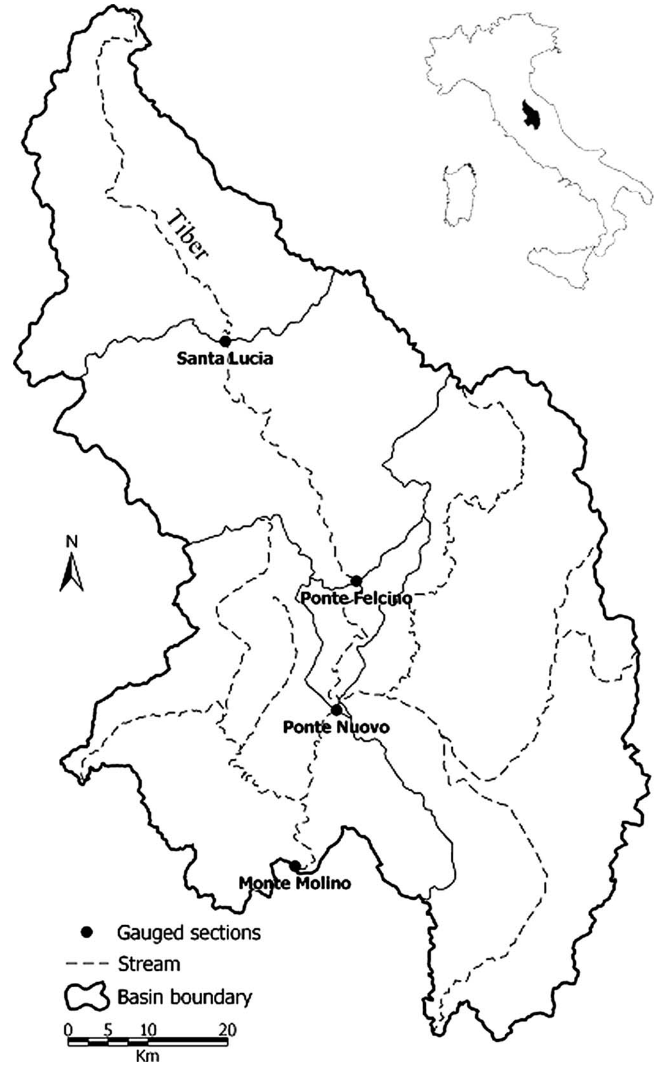

Fig. 2. Upper Tiber River basin with the location of the gauging sites and the related subtended drainage areas

Moramarco et al. (2005) assessed the linear relationship expressed by Eq. (2) using several different flood events characterized by different magnitude and duration. They produced the scatter plots of $[A_d(t)]/[A_u(t-T_L)]Q_u(t-T_L)$ versus $Q_d(t)$ for each selected event and found out that there is a very strong linear relation between these two variables regardless of the magnitude of the lateral inflow contribution. Hence, Eq. (2) can be considered as a physically based model.

Parameters α and β are estimated from the following equations utilizing base flow and peak discharge at the boundary sections of the selected river reach (Moramarco and Singh 2001):

$$Q_d(t_b) = \alpha \frac{A_d(t_b)}{A_u(t_b-T_L)} Q_u(t_b-T_L) + \beta \tag{3a}$$

$$Q_d(t_p) = \alpha \frac{A_d(t_p)}{A_u(t_p-T_L)} Q_u(t_p-T_L) + \beta \tag{3b}$$

where $Q_d(t_b)$=base flow rate at the downstream section; $Q_d(t_p)$ =peak discharge at the downstream section; t_p and t_b=times when the peak stage and baseflow occurs at the downstream section,

J. Hydrol. Eng., 2009, 14(5): 463-474.

Table 1. Main Geomorphological Characteristics of Tiber River Reaches

River	Bounded sections	Drainage area (km^2)	Reach length (km)	Mean slope	Mean width (m)
Tiber	Santa Lucia	935	44.6	0.0016	35
	Ponte Felcino	2,035			
Tiber	Santa Lucia	935	70	0.0014	39
	Ponte Nuovo	4,145			
Tiber	Santa Lucia	935	100.8	0.0012	44
	Monte Molino	5,279			

respectively. In particular, t_b is assumed to be the time just before the start of the rising limb of the hydrograph.

Base flow rate $Q_d(t_b)$ can be computed from the velocity measurements during low flows or it can be computed as the product between the upstream mean velocity that is estimated through $Q_u(t_b - T_L)$ and the downstream flow area $A_d(t_b)$, assuming that the mean velocity is constant between upstream and downstream sections. Although this assumption may result in errors in the computation of base flow rate, this has negligible influence on reconstructing the downstream discharge hydrograph for high stages that are of most interest in hydrological practice (Moramarco et al. 2005). The peak discharge $Q_d(t_p)$ is surmised as the contribution of two main elements: (a) the upstream discharge delayed for the wave travel time T_L, $Q_u(t_p - T_L)$, with its attenuation Q^* due to flood routing along the reach of length L; and (b) the lateral inflows $q_p L$ during the time interval $(t_p - T_L, t_p)$

$$Q_d(t_p) = (Q_u(t_p - T_L) - Q^*) + q_p L \tag{4}$$

In Eq. (4), T_L is implicitly assumed as the time to match the rising limb and the peak region of the upstream and downstream dimensionless hydrographs. The flood attenuation Q^* is computed from the Price formula (Raudkivi 1979). The lateral inflow contribution $q_p L$ is obtained from the solution of the characteristic form of the continuity equation (Moramarco et al. 2005). In particular, q_p is estimated by assuming that along the characteristic corresponding to the downstream peak stage, the following relationship holds (Moramarco and Singh 2002):

$$\frac{A_d(t_p) - A_u(t_p - T_L)}{T_L} = q_p \tag{5}$$

Once $Q_d(t_b)$ and $Q_d(t_p)$ are known, parameters α and β are obtained from the solution of Eqs. (3*a*) and (3*b*). Note that, for each event observed even in the same river reach, one needs to obtain a different set of α and β values. Moreover, for each event one needs to estimate the wave travel time. The estimation of wave travel time is given in Moramarco et al. (2005).

Since the parameter values change according to flood events, the RCM model is not suitable for applications in a context of discharge monitoring in real time. Furthermore, due to its calibration procedure, apart from the upstream peak discharge, the information on base flow condition and the peak stage at the downstream end has to be provided.

On the other hand, by the application of the GA technique to the RCM model, henceforth named GA-RCM model, for each river reach a single set of optimal parameter values can be used regardless of the magnitude of flood events, thus, making the GA-RCM model a practical tool for real time discharge monitoring.

GA-RCM Model Application

Watershed and Hydrologic Data

The GA-RCM model was tested on three equipped river reaches of the Upper Tiber River in central Italy. Fig. 2 shows the location of the selected hydrometric sections defining the investigated branches along with subtended drainage areas. Table 1 summarizes the main characteristics of the selected river reaches. Each gauged section is equipped with a remote ultrasonic water level gauge, and velocity measurements are carried out by current meter. Several accurate flow measurements were available, which allowed the estimation of the rating curve for each section (Moramarco et al. 2005).

Severe storm events that occurred in the three different reaches were considered for GA-RCM model calibration and testing. The main properties of the selected flood events are summarized in Tables 2, 3, and 4. It is seen that the lateral inflow contribution was significant in most of the events. Table 2 presents the storm events observed at Santa Lucia and Ponte Felcino gauged sections, Table 3 presents the storm events observed at Santa Lucia and Ponte Nuovo sites, and Table 4 shows the events occurred at Santa Lucia and Monte Molino equipped sections. Moreover,

Table 2. Main Characteristics of Flood Events Observed at Santa Lucia and Ponte Felcino Stations

	Santa Lucia station			Ponte Felcino station			RCM			GA		
Date	Q_b (m^3/s)	Q_p (m^3/s)	V (10^6 m^3)	Q_b (m^3/s)	Q_p (m^3/s)	V (10^6 m^3)	T_L (h)	α	β	T_L (h)	α	β
Dec. 1990	9	394.7	46.5	5	404.2	56.8	2	1.16	−7.7	**4**	**1.20**	**−5.96**
Jan. 1994	40	112.0	9.2	50.8	240.7	17.8	2.5	1.72	−44.8			
May 1995*	4.4	79.4	13.1	10	138.7	19.1	4	1.17	−3.50			
Jan. 1997*	18.8	121.8	25.2	36.2	225.1	51.8	3.5	1.32	−10.2			
		142.1			359.3							
June 1997*	4.4	327.2	27.2	10.8	449.6	49.1	3	1.19	−3.50			
Jan. 2003	25.7	45.6	14.5	49.3	113.4	38.2	3.5	1.32	−13.05			
		65.9			223.8							
Feb. 2004*	24	98.5	14.2	55.3	277.6	43.6	3.5	1.38	−13.5			
		54.8			153.2							
					Mean values		**3.1**	**1.32**	**−13.8**			

Note: Q_b = base flow; Q_p = peak flow; V = volume; T_L = wave travel time; α and β = RCM parameters.

J. Hydrol. Eng., 2009, 14(5): 463-474

Table 3. Main Characteristics of Flood Events Observed at Santa Lucia and Ponte Nuovo Stations

	Santa Lucia station			Ponte Nuovo station			RCM			GA		
Date	Q_b (m^3/s)	Q_p (m^3/s)	V (10^6 m^3)	Q_b (m^3/s)	Q_p (m^3/s)	V (10^6 m^3)	T_L (h)	α	β	T_L (h)	α	β
Dec. 1996	14	268.9	21.2	58.9	730.4	64.7	8.5	1.02	−21.6	**8**	**1.02**	**36.99**
Apr. 1997*	3.4	346.1	31.0	16.5	500.5	67.1	8.5	1.05	−11			
Dec. 1998*	26	56	8.3	77.8	716.8	52.4	9.5	1.02	−31			
Feb. 1999	16	219.1	14.9	42.6	763.8	68.4	8	1.13	−34.3			
Mar. 2000*	5.6	61.6	11.8	34	370.7	85.7	9.5	1.42	−30			
Dec. 2000*	4.7	202.5	51.3	24.3	451.5	198.8	7.5	1.12	−14			
		330.5			879.2							
Jan. 2001*	22	72	14.2	106	404.5	67.5	7.5	1.38	−67			
		72.6			312.1							
						Mean values	**8.4**	**1.16**	**−29.8**			

Note: Q_b=base flow; Q_p=peak flow; V=volume; T_L=wave travel time; α and β=RCM parameters.

the wave travel time, and α and β parameter values used by the RCM model for each event are also shown in these tables, with the events that are used for model calibration by the GA being marked by *. For each reach, four events were used for GA-RCM model calibration and three were used for model testing. For each river reach, the events were randomly grouped for calibration and application so as to avoid the bias in model performance. The wave travel time, on the average, is 4, 8, and 12 h for Santa Lucia-Ponte Felcino reach, Santa Lucia-Ponte Nuovo reach, and Santa Lucia-Monte Molino reach, respectively (Tables 2–4) and these values were used in the calibration of the GA-RCM models.

GA-RCM Model Implementation and Calibration

According to Eq. (2), the GA-RCM model obtains the optimal values of the model parameters α and β by using the information of discharge and effective cross-sectional flow area at the upstream end of the selected reach and discharge and effective cross-sectional flow area (wave travel time later) at the downstream station.

The GA obtained optimal model parameters of the RCM by minimizing the mean-absolute error (MAE) function (objective function) of the form

$$\mathrm{MAE}=\frac{1}{N}\sum_{i=1}^{N}|Q_m-Q_p| \qquad (6)$$

where N=number of observations; Q_m=measured flow discharge; and Q_p=predicted flow discharge.

The MAE, illustrating the possible maximum deviation, is one of the commonly employed error functions in the literature (Chang et al. 2005). According to Taji et al. (1999), to minimize the deviation, the absolute error may sometimes be better than the square error. In fact, the absolute error function has the advantage that it is less influenced by anomalous data than the square error function (Taji et al. 1999).

We need to emphasize that for the standard RCM model, the calibration procedure is not based on objective functions. In fact, Eqs. (3)–(5) are applied for the calibration without considering any minimization algorithm and performances are assessed a posteriori through accuracy measure indices such as peak discharge errors and the Nash-Sutcliffe coefficient (Moramarco et al. 2005).

Initially, the parameters were randomly assigned values in the range [0–5]. The GA employed 100 chromosomes in the initial gene pool, 75% crossover rate, and 5% mutation rate and 10,000 iterations. The range for α parameter in Eq. (2) was constrained

Table 4. Main Characteristics of Flood Events Observed at Santa Lucia and Monte Molino Stations

	Santa Lucia station			Monte Molino station			RCM			GA		
Date	Q_b (m^3/s)	Q_p (m^3/s)	V (10^6 m^3)	Q_b (m^3/s)	Q_p (m^3/s)	V (10^6 m^3)	T_L (h)	α	β	T_L (h)	α	β
Apr. 1997	3.2	346.1	32.6	29.4	572.0	96.80	13	0.95	−4.8	**12**	**1.08**	**−21.50**
Dec. 1998*	26.3	56.0	7.2	85.7	769.8	59.65	11	1.22	−60			
Feb. 1999*	11	229	15.2	45	754	80.7	12.5	1.02	−7.6			
Dec. 2000	3.4	202.5	53.1	26.4	507.2	224.4	11.5	1.05	−8.5			
		330.5			850.1							
Jan. 2001	23	72.0	15.9	120	397.3	84.8	11.5	1.14	−36			
		72.6			364.1							
Apr. 2001*	24	143	9.6	50	272	21.4	11.0	2.17	−147			
May 2004*	10	121.8	45.6	70	544.4	188.5	11.5	1.06	−14.4			
		239.1			536.5							
						Mean values	**11.7**	**1.23**	**−39.7**			

Note: Q_b=base flow; Q_p=peak flow; V=volume; T_L=wave travel time; α and β=RCM parameters.

J. Hydrol. Eng., 2009, 14(5): 463-474

in $[-5-5]$ while the range for β parameter was constrained in $[-50-50]$ for each iteration. The trial version of evolver GA solver for Microsoft Excel (Palisade Corporation 2001) was employed in this study. The algorithm employs the *recipe solving method* to minimize the objective function under specified constraints (Palisade Corporation 2001). It takes a very short CPU time, in the order of a couple of min, to run the program for thousands of iterations with hundreds of chromosomes in the gene pool.

Note that, in order to start computations, random values must be assigned to the model parameters. As the model performs iterations while reaching a global error, the values of parameters are updated each iteration. Thus, the effect of initially assigned values diminishes as the number of iterations increases. With regard to the ranges assigned to the parameters, we benefited from the studies of Moramarco and Singh (2001) and Moramarco et al. (2005) where α varied in $[0.5–3]$ and β varied in $[10--65]$.

Four events (marked by *) reported in Table 2 were used for calibrating the model parameters for the Santa Lucia-Ponte Felcino reach by the GA. The calibrated values were found to be $\alpha=1.20$ and $\beta=-5.96$ (Table 2). These values are comparable with those average values obtained by the RCM model (Table 2). Note that, as pointed out earlier, unlike the GA-RCM model, the RCM finds different sets of values for the parameters and uses different wave travel times for each event.

In a similar fashion, four events (marked by *) from Tables 3 and 4 events (marked by *) from Table 4 were employed to calibrate the parameters for Santa Lucia-Ponte Nuovo reach and Santa Lucia-Monte Molino reach, respectively. The calibrated parameter values were found to be $\alpha=1.02$ and $\beta=36.99$ (Table 3) for the first reach. Although the value of α may be considered comparable with the average value of α obtained by the RCM, the value of β is quite different (Table 3). For Santa Lucia-Monte Molino reach, the optimal parameter values were found to be $\alpha=1.08$ and $\beta=-21.50$ (Table 4) that are comparable with the average ones obtained by the RCM model application.

Hence, in this study, we applied GA to several events simultaneously (four events for each river reach; see Tables 2–4) to obtain optimal parameter values of the RCM model for each river reach. Hence, the GA-RCM model would use only one set of optimal parameter values for all the events observed in the same river reach.

Hydrograph Predictions

In the following prediction, results as discussed above, the GA-RCM model refers to the RCM model whose parameters were optimized by the genetic algorithm. On the other hand, the RCM model refers to the standard RCM model expressed by Eq. (2), whose parameters were obtained by Eqs. (3)–(5).

River Reach Santa Lucia-Ponte Felcino

Fig. 3 presents simulations of three hydrographs measured at Ponte Felcino station by the GA-RCM and RCM models. We point out that the intermediate basin is greater than 100% of the upstream subtended one (see Table 1). For the RCM model, the traditional procedure for estimating α and β parameters was adopted. Note that outflow hydrographs are observed at Ponte Felcino downstream station. As seen in Fig. 3, both the models performed equally well in simulating the event observed in Dec. 1990 [Fig. 3(a)]. However, the GA-RCM model outperformed the RCM in simulating the other two events [Figs. 3(b and c)]. While the GA-RCM model showed an excellent performance in capturing the trend, time to peak, and the peak rates of the hydrographs, the RCM overpredicted the peak discharges [Figs. 3(b and c)].

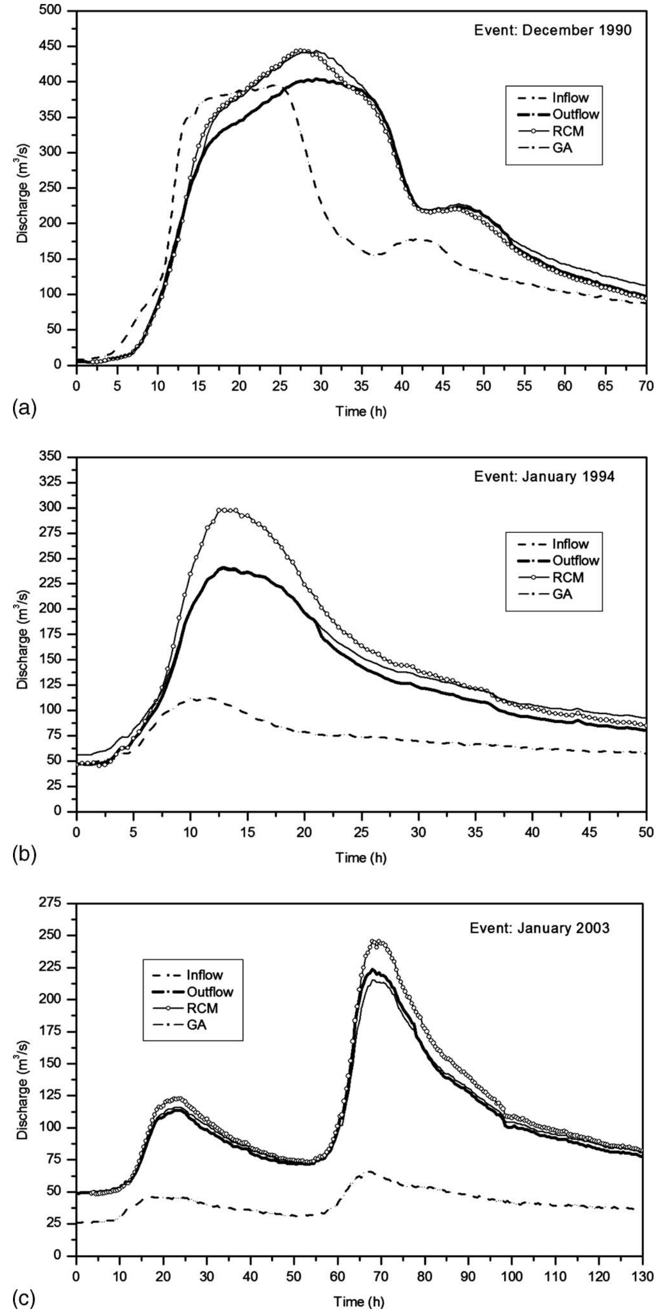

Fig. 3. GA and RCM model simulations of the flood hydrographs measured at Ponte Felcino gauging station in (a) Dec. 1990; (b) Jan. 1994; and (c) Jan. 2003; discharge hydrograph (inflow) observed at Santa Lucia section is also shown

The percentage error in peak discharge and the error in time to peak were computed for each event and are given in Table 5. Note that, in the case of peak rate, a negative error value indicates underestimation, whereas a positive value indicates overestimation. In the case of time to peak, a negative error value indicates early rise in reaching the peak rate while a positive value indicates delay. According to Table 5, GA-RCM and RCM models overpredicted the peak discharge of the Dec. 1990 event with about 10% error. The GA-RCM model predicted the peak rates of the other two events with less than 4% error, while RCM had, on

Table 5. Percentage Errors in Peak Discharge [E_{Qp}] and Time to Peak [E_{Tp}] for the Events Observed at Ponte Felcino Station (Fig. 3), Ponte Nuovo Station (Fig. 4), and Monte Molino Station (Fig. 5)

	E_{Qp} (%)		E_{Tp} (h)	
Event	GA	RCM	GA	RCM
	Ponte Felcino station			
Dec. 1990	9.80	9.85	0.0	−2.0
Jan. 1994	−0.54	23.54	0.0	−0.5
Jan. 2003	2.20	8.08	0.0	0.0
	−3.75	9.67	0.0	0.0
Average	**4.08**	**12.78**	**0.0**	**0.62**
	Ponte Nuovo station			
Dec. 1996	5.53	6.27	−2.5	0.0
Feb. 1999	−1.64	12.07	−3.5	−2.5
Jan. 2001	−11.77	19.53	−0.5	0.0
	−12.01	8.64	5.0	5.0
Average	**7.72**	**11.62**	**2.88**	**1.88**
	Monte Molino station			
Apr. 1997	−0.98	−12.76	−2.0	−1.0
Dec. 2000	−1.15	3.08	0.0	−4.5
	−1.93	7.07	−10.0	−11.5
Jan. 2001	−0.06	3.46	0.0	0.0
	−1.16	3.53	1.5	2.5
Average	**1.06**	**5.98**	**2.7**	**3.9**

average, about 14%. Especially the peak rate of Jan. 1994 was almost exactly predicted by the GA-RCM model, while RCM overpredicted the peak discharge with about 24% error. The time to peak for each event was exactly predicted by the GA-RCM model, while RCM had, on the average, 0.62 h error (Table 5).

River Reach Santa Lucia-Ponte Nuovo

Fig. 4 presents simulations of three hydrographs measured at Ponte Nuovo station by the GA-RCM and RCM models. As can be seen, both the models performed satisfactorily in simulating the hydrographs. They were able to overall capture the trend, time to peak, and peak rates. The percentage errors in peak discharge and the error in time to peak for Fig. 4 were computed for each event and are given in Table 5. According to Table 5, the GA-RCM model and the RCM method overpredicted the peak discharge of the Dec. 1996 event with an error equal to 5.5 and 6.3%, respectively. The GA-RCM model predicted the peak rates of the event occurring in Feb. 1999 with less than about 2% error, while RCM had about 12%. As regards the flood of Jan. 2001, it has to be underlined that the GA-RCM model underpredicted both the peaks with an error of about 12%, while RCM overestimated the first peak with an error of about 20% and the second one with an error less than 9%. With respect to the time to peak, the GA-RCM model on the average yielded an error of about 3 h, while RCM provided a lower error, which was found less than 2 h. In this case, we also need to emphasize that these errors can be favorably accepted considering that the intermediate basin is three times the upstream subtended one.

River Reach Santa Lucia-Monte Molino

Fig. 5 presents simulations of three hydrographs observed at Monte Molino station by the GA-RCM and RCM models. As seen in Fig. 5, both the models performed satisfactorily in simulating hydrographs observed in Jan. 2001 and Dec. 2000 [Figs. 5(b and c)], although RCM slightly overestimated the peaks of both the hydrographs. The GA-RCM model showed an excellent performance in simulating the Apr. 1997 event in terms of trend, time to peak and peak rate, while the RCM underpredicted the peak discharge of the hydrograph [Fig. 5(a)]. The percentage errors in peak discharge and time to peak for Fig. 5 were computed for each event and are given in Table 5. According to Table 5, the GA-RCM model predicted peak discharge for each event with less than 2% error, while RCM, on the average produced 6% error. With regard to the time to peak, the GA-RCM model predicted exact peak timing for the first peak of Dec. 2000 and for the first one of Jan. 2001. The RCM model had, on the

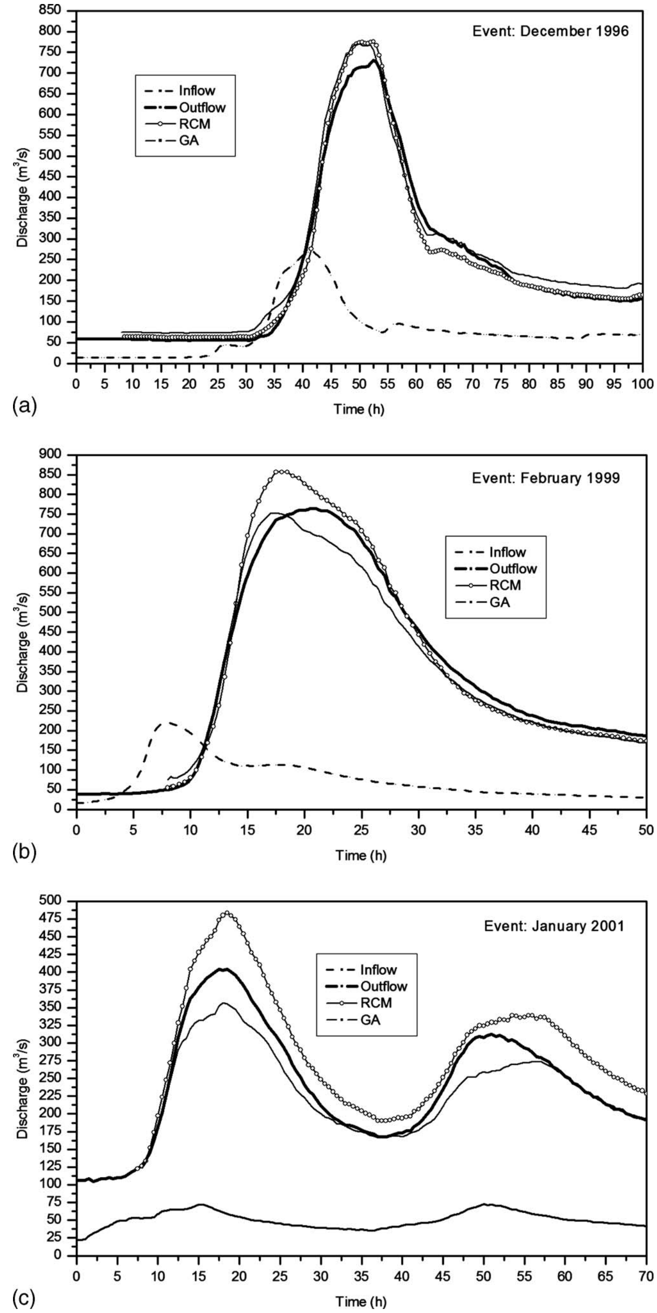

Fig. 4. GA and RCM model simulations of the flood hydrographs measured at Ponte Nuovo gauging station in (a) Dec. 1996; (b) Feb. 1999; and (c) Jan. 2001; discharge hydrograph (inflow) observed at Santa Lucia section is also shown

J. Hydrol. Eng., 2009, 14(5): 463-474

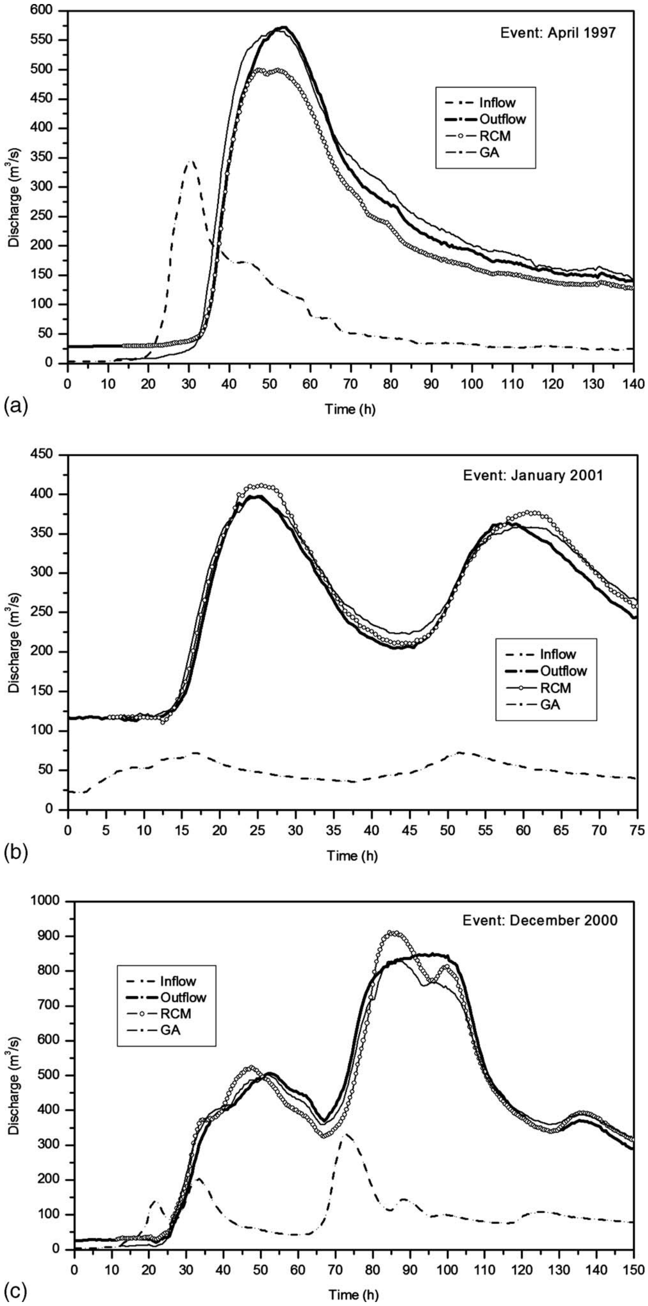

Fig. 5. GA and RCM model simulations of the flood hydrographs measured at Monte Molino gauging station in (a) Apr. 1997; (b) Jan. 2001; and (c) Dec. 2000; discharge hydrograph (inflow) observed at Santa Lucia section is also shown

average, an error equal to 3.9 h (Table 5). It should be underlined that both models reached the second peak observed in Dec. 2000 earlier with an error of 10 and 11.5 h (Table 5).

We further analyze the GA-RCM model performance against RCM using additional error measures of MAE and the Nash-Sutcliffe (NS) efficiency index. As pointed out earlier, MAE is one of the commonly employed error functions in the literature (Chang et al. 2005). According to Taji et al. (1999), it has the advantage of being less influenced by anomalous data than the square error functions. The NS index is also a commonly employed goodness-of-fit parameter (ASCE 1993; Kalin et al. 2003; Bardossy 2007), among others, that can be applied to a variety of models (McCuen et al. 2006).

Table 6. Mean Absolute Error (MAE) (m^3/s) and Nash-Sutcliffe (NS) Efficiency Index Values for GA and RCM Models

	MAE (m^3/s)		NS (%)	
Event	GA	RCM	GA	RCM
	Santa Lucia-Ponte Felcino			
Dec. 1990	12.9	10.4	98	98
Jan. 1994	9.3	14.5	97	84
Jan. 2003	3.1	6.9	99	96
Average	**8.4**	**10.6**	**98**	**93**
	Santa Lucia-Ponte Nuovo			
Dec. 1996	26.7	17.0	98	99
Feb. 1999	32.8	31.1	97	96
Jan. 2001	19.2	36.8	85	79
Average	**26.2**	**28.3**	**93**	**91**
	Santa Lucia-Monte Molino			
Apr. 1997	16.9	23.0	98	96
Dec. 2000	27.9	34.7	98	97
Jan. 2001	12.7	11.1	97	97
Average	**19.1**	**22.9**	**98**	**97**

Table 6 presents the computed MAE and NS index values for the application events in Figs. 3–5 for the three reaches. As seen for Santa Lucia-Ponte Felcino reach, the GA-RCM model produced less MAE (on the average 8.4 m^3/s) and higher NS index (about 98%) than the RCM model for each event. Especially for the Jan. 1994 event [Fig. 3(b)], the GA-RCM model showed significantly better efficiency (NS=97%) than RCM (NS=84%). A similar performance was observed for Santa Lucia-Ponte Nuovo reach. As seen in Table 6, the GA-RCM model yielded less MAE (on the average 26.2 m^3/s) and higher NS (on the average 93%) than the RCM model (on the average MAE=28.3 m^3/s and NS=91%). Especially for the Jan. 2001 event [Fig. 4(c)], the error produced by the RCM is about twice that by the GA-RCM model and it had a lower efficiency of NS=79%, as opposed to NS=85% by the GA-RCM model. Both the models produced comparable good performance for the events observed at Monte Molino station (Table 6) with, on the average, about MAE=21 m^3/s and more than 97% efficiency. Although the GA-RCM model showed slightly better performance than RCM for this reach, it did not significantly outperform the RCM, as it was the case for the other two river reaches. This might be due to the fact that the GA-RCM model employs an average wave travel time for each event, as opposed to the exact wave travel time required by the RCM. As the distance between upstream and downstream stations increases, and, hence, the intermediate basin area, the assumed average wave travel between the two stations might not be very representative for each event. However, when one considers that the intermediate basin is about 4,300 km^2 (85% of the whole basin) for Santa Lucia-Monte Molino river reach, the performance of the GA-RCM model could then be recognized as very satisfactory. When the computed MAE and NS values for all the events for all three river reaches in Table 6 are evaluated, the GA-RCM model, overall, produced less MAE (on the average 17.9 m^3/s) than the RCM, which had 20.6 m^3/s of MAE. In other words, the RCM produced about 15% more error than the GA-RCM model. The GA-RCM model, overall, also had an efficiency equal to about 96%, which is slightly greater than the average NS index of the RCM model, equal to 94%.

J. Hydrol. Eng., 2009, 14(5): 463-474

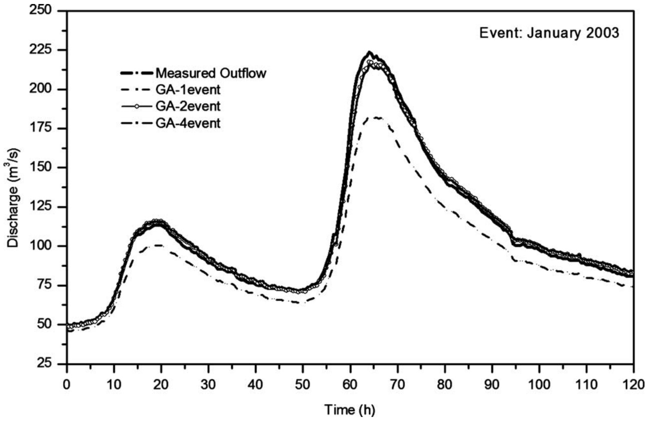

Fig. 6. Simulation of Jan. 2003 outflow hydrograph observed at Santa Lucia-Ponte Felcino reach by GAs using one, two, and four events in the calibration

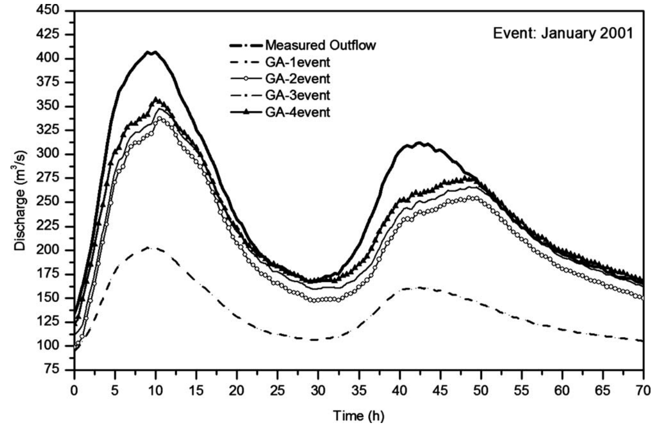

Fig. 7. Simulation of Jan. 2001 outflow hydrograph observed at Santa Lucia-Ponte Nuovo reach by GAs using one, two, three, and four events in the calibration

The above results show that the GA optimized RCM model successfully simulated hydrographs at each river reach having different wave travel time and lateral inflows. It closely captured the trends, time to peak, and peak rates with, on the average, less than 5% error. It also outperformed the standard RCM, which, on the contrary to the GA-RCM, used different values of model parameters and wave travel times for each event.

Sensitivity Analysis

Number of Events Used in Calibration

As presented earlier, for each river reach, four out of seven events were employed to calibrate the model parameters by the genetic algorithm. In this section, we investigate the minimum number of events that might be required by the GA-RCM to obtain the optimal values of the model parameters during the calibration procedure.

For Santa Lucia-Ponte Felcino reach, the May 1995 event (Table 2) was first used in the calibration (one-event case) and then May 1995 and Jan. 1997 (Table 2) were together used in the calibration (two-event case). These cases were compared with the measured hydrographs and the four-event case (* marked events in Table 2 were used in the calibration). Although three test simulations were performed (Jan. 2003, Dec. 1990, and Jan. 1994 in Table 2), for the sake of brevity, in Fig. 6 we show only the simulation of a flood event that occurred in Jan. 2003. As seen, the two-event case performs as good as the four-event case. Similar results were also obtained for the other two simulations for the two-event case. The one-event case, in general, performed poorly. It underpredicted the peak rate with, on the average, 14% error. However, it exactly predicted the time to peak for each event with 0% error.

Fig. 7 shows the simulation of the Jan. 2001 event observed at the river reach of Santa Lucia-Ponte Nuovo by GA-RCM using one, two, three, and four events at the calibration stage. Apr. 1997 (Table 3) was first used in the calibration (one-event case), then Apr. 1997 and Dec. 2000 (Table 3) were together used in the calibration (two-event case), then Apr. 1997, Dec. 2000, and Mar. 2000 (Table 3) all together were used in the calibration (three-event case) and finally events marked by * in Table 3 were used in the calibration (four-event case). Although three test simulations were performed (Feb. 1999, Dec. 1996, and Jan. 2001 in Table 3), for the sake of brevity, we show only one of them in Fig. 7, which shows the simulation of the Jan. 2001 event. As seen in Fig. 7, two-, three-, and four-event cases perform almost equally well in simulating the hydrograph while the one-event case performs poorly. In general, the one-event case, reached the peak of events earlier, on the average, with about 10% error and underpredicted the peak rates with 19% error. This result also implies that for this reach having 8 h wave travel time, two events are sufficient to obtain the optimal model parameters.

For the Santa Lucia-Monte Molino reach, the Feb. 1999 (Table 4) event was used in the calibration (one-event case). With the calibrated model, the other three events in Table 4 (Apr. 1997, Dec. 2000, and Jan. 2001) were simulated. Fig. 8 shows the simulation of the Dec. 2000 event. As seen, the one-event case performs as good as the four-event case. Similar simulation results were also obtained for the other two hydrographs in the case of using the one-event case. The one-event-case in each simulation captured the time to peak exactly with 0% error and peak rates, on the average, with less than 3% error.

From the above results, it may be stated that although using one event for the calibration was sufficient for the Santa Lucia-Monte Molino reach, it had poor performances for the other two

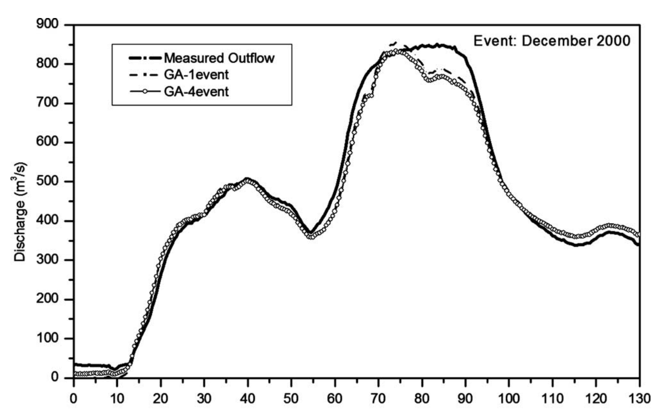

Fig. 8. Simulation of Dec. 2000 outflow hydrograph observed at Santa Lucia-Monte Molino reach by GAs using one and four events in the calibration

J. Hydrol. Eng., 2009, 14(5): 463-474

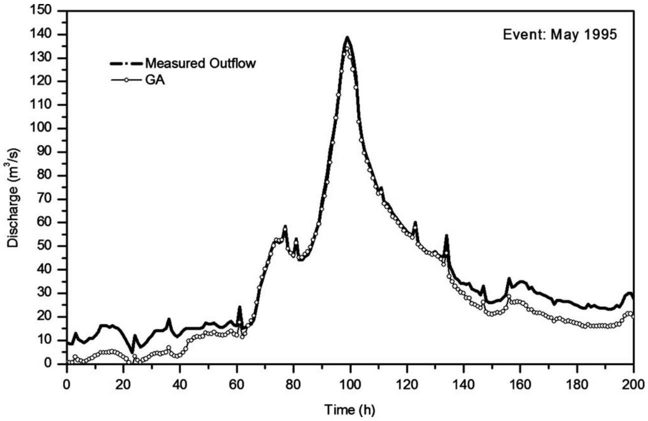

Fig. 9. Simulation of May 1995 outflow hydrograph observed at Santa Lucia-Ponte Felcino reach

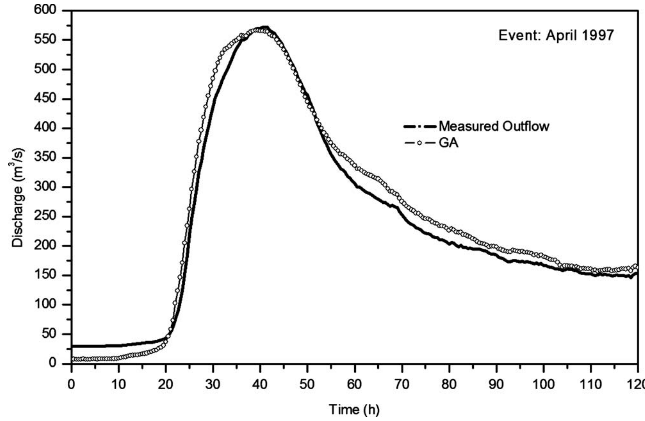

Fig. 11. Simulation of Apr. 1997 outflow hydrograph observed at Santa Lucia-Monte Molino reach

river reaches. Therefore, to be on the safe side, we may suggest employing at least two events for the calibration of the RCM model parameters α and β by the GA algorithm.

Using Shorter Wave Travel Time Events in the Calibration

In this section, we investigate employing events that might have shorter wave travel times in the calibration of the model parameters by the GA and then testing the so-obtained parameters to simulate hydrographs having longer wave travel times.

As shown in the previous section, since two events would be sufficient to calibrate the model parameters, the Dec. 1990 event, which has 2 h wave travel time and the Jan. 1994 event, which has 2.5 h wave travel time (Table 2) were used in the calibration for the Santa Lucia-Ponte Felcino reach. Fig. 9 shows the simulation of the May 1995 event whose wave travel time is 4 h (Table 2). As seen, the GA-RCM performed quite satisfactorily in capturing the trend, time to peak (0% error), and peak rate (3.5%). Note that the wave travel time of the May 1995 event used for testing is almost twice longer than those of the events used in calibration.

For the Santa Lucia-Ponte Nuovo reach, the Dec. 2000 and Jan. 2001 events, which have 7.5 h wave travel times (Table 3) were employed in the calibration. Fig. 10 shows the simulation of the Dec. 1998 event whose wave travel time is 9.5 h (Table 3). As seen, the model was able to capture the trend and the time to peak of the hydrograph, although it underestimated the peak rate with about 24% error. Note that the travel time of the testing event is 26% longer than those of the events used in calibration.

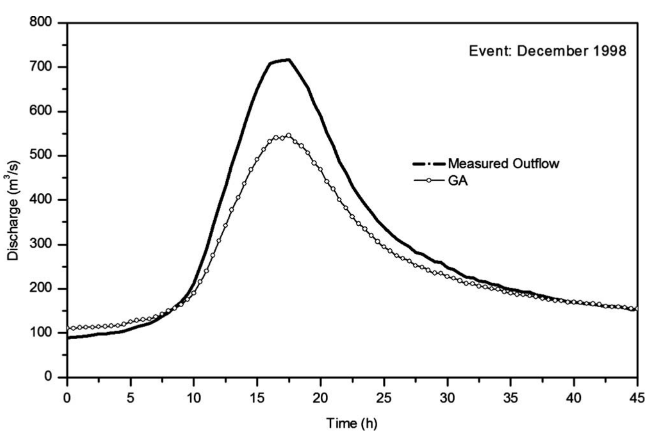

Fig. 10. Simulation of Dec. 1998 outflow hydrograph observed at Santa Lucia-Ponte Nuovo reach

The May 2004 and Jan. 2001 events, each having 11.5 h wave travel time (Table 4), were employed in calibrating model parameters by the GA for the Santa Lucia-Monte Molino reach. Fig. 11 presents the simulation of the Apr. 1997 event whose wave travel time is 13 h (Table 4). As seen, the model captured the trend, time to peak (0% error), and peak rate (1.0% error) satisfactorily.

From the above results, it may be stated that one can find optimal values of the RCM model parameters by the GA using short-wave travel time events to predict events that may have longer wave travel times.

Using Lower Peak Events in Calibration

Tayfur et al. (2007) investigated the extrapolation capability of ANN in predicting flood hydrographs. They trained ANNs with lower peak hydrographs and tested them against higher peaked ones. They found out that the percentage prediction error in peak discharge varies exponentially with the difference between the peak discharge used in training and the peak discharge used in testing. For example, they showed that when an event whose peak discharge is 100 m^3/s is used in network training to predict an event whose peak discharge is 200 m^3/s, peak discharge is underpredicted with a 50% error. This prediction error would be about 10, 15, or 25% if the peak discharge to be predicted were 110, 120, or 140 m^3/s, respectively. In this section, we would like to investigate the extrapolation capability of GA-RCM to see whether it has the same shortcomings as ANN. To do so, for each reach, we obtain the optimal values of model parameters using lower peak events and then simulate the higher peak hydrographs.

The May 1995 event (whose peak is 138.7 m^3/s) and the Jan. 2003 event (whose peak is 223.8 m^3/s) (Table 2) from the Santa Lucia-Ponte Felcino reach were employed for calibrating model parameters by the GA. Fig. 12 shows the simulation of the June 1997 event whose peak discharge is 449.6 m^3/s (Table 2). As seen, the model showed a good performance in capturing the trend, time to peak (0% error), and the peak (3.2% error) of the measured hydrograph. Note that the peak rate predicted is twice more than the peak of the events used in the calibration.

The Mar. 2000 event (whose peak is 370.7 m^3/s) and the Jan.

J. Hydrol. Eng., 2009, 14(5): 463-474

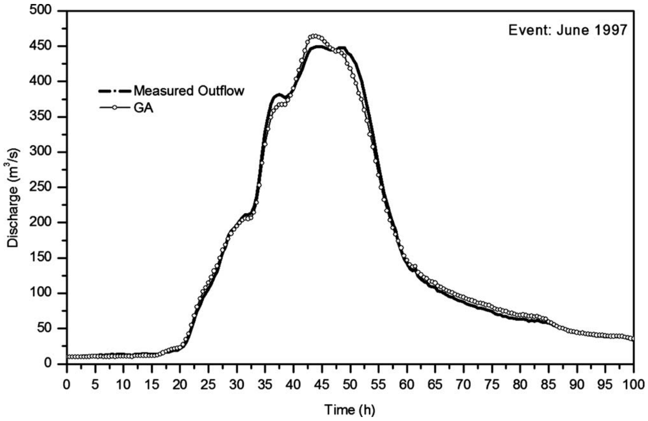

Fig. 12. Simulation of June 1997 outflow hydrograph observed at Santa Lucia-Ponte Felcino reach

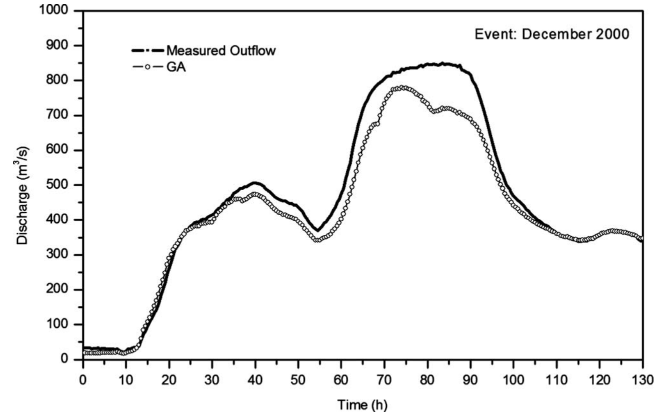

Fig. 14. Simulation of Dec. 2000 outflow hydrograph observed at Santa Lucia-Monte Molino reach

2001 event (whose peak is 404.5 m^3/s) (Table 3) were employed in calibrating the model parameters by GA for the Santa Lucia-Ponte Nuovo reach. Fig. 13 shows the simulation of the Dec. 2000 event whose peak rate is 879.2 m^3/s (Table 3). As seen, the model satisfactorily simulated the hydrograph with a delay in reaching the peak rate equal to 4.5 h and overestimated the peak with less than 15% error. Note that the peak rate predicted is twice more than the peak of the events used in the calibration.

For the Santa Lucia-Monte Molino reach, the Jan. 2001 event (whose peak is 397.3 m^3/s) and Apr. 2001 event (whose peak is 272 m^3/s) (Table 4) were used in the calibration and then the Dec. 2000 event (whose peak is 850.1 m^3/s) (Table 4) was employed for testing. As seen in Table 4, the peak of the tested hydrograph is almost three times the peak of the hydrographs used for calibrating the model parameters. Fig. 14 shows the simulation of the Dec. 2000 hydrograph. As seen, the model satisfactorily captured the trend of the hydrograph. It reached the peak 9.5 h earlier and underpredicted the peak with 8% error.

The above results imply that the GA-RCM model, unlike the ANNs, does not have an extrapolation problem. It can be calibrated with lower peak events to predict higher peak hydrographs.

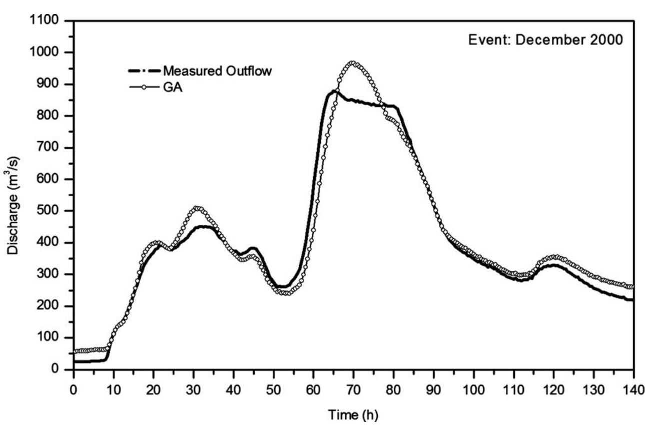

Fig. 13. Simulation of Dec. 2000 outflow hydrograph observed at Santa Lucia-Ponte Nuovo reach

Conclusions

The following conclusions are drawn from this study:

1. RCM model whose parameters were optimized by the genetic algorithm, named hereafter as the GA-RCM model, successfully simulated event-based individual storm hydrographs having different wave travel times and magnitude of lateral inflows at each river reach of the Upper Tiber River basin in central Italy. For whatever intermediate basin area, it closely captured the trends, time to peak, and peak rates of the storms with, on the average, less than 5% error.
2. The GA-RCM model, in general, outperformed the standard RCM in predicting hydrographs with respect to, especially, peak rate and time to peak, although it required far less input data. The standard RCM produced larger errors although, on the contrary to the GA-RCM, it used different values of model parameters and wave travel times for each event.
3. The proposed methodology of discharge estimation is useful for the present day hydrological practices, especially when many river gauging sites are abandoned due to funding requirements for maintaining the stations. If geomorphologic changes along a river reach are not significant, one can establish a discharge measuring site for 3 to 4 years and then convert the site only for measuring the stage hydrographs and, thereby, enabling the proposed methodology for estimating discharges at these sites.
4. The results of sensitivity analysis indicate that two events would be sufficient for the GA-RCM model in calibration to obtain optimal model parameters.
5. Shorter wave travel time events can be used in calibration to obtain optimal model parameters by the GA-RCM model that, in turn, can be employed to predict hydrographs having longer wave travel times.
6. The GA-RCM model, unlike ANN, does not have an extrapolation problem. It can be calibrated with lower peak events to predict higher peak hydrographs.

The main novelty of this study is to address the applicability of the standard RCM model for the discharge monitoring in real time at river sites where only water levels are observed and the rating curve is unknown. For the standard RCM model, this target is not reachable because of its parameters assessment procedure. In fact, discharge and stage hydrographs at upstream and downstream end, respectively, need to be observed, at least until the peak phase, to obtain a reliable estimation of parameter values. On the other hand, through the GA-RCM model, this drawback is overcome by providing a single set of parameter values for an investigated river reach, regardless of magnitude of a flood event. Another aspect that should be emphasized is that providing constant parameter values for a river reach addresses the applicability of the GA-RCM model also for ungauged river reaches with similar morphological characteristics of those investigated here. This insight could be the target of future work.

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J. Hydrol. Eng., 2009, 14(5): 463-474