# Impact of Hydrologic Uncertainties in Reservoir Routing

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## *Abstract*

*Reservoir routing methods are used in the design and operation of storage facilities at high flow conditions. Traditionally, deterministic approaches have been used for reservoir flood routing computations, which do not account for possible variations in governing parameters. However, hydrologic variables, such as inflow, stage, and outflow may naturally have various sources of uncertainties. Since important dimensions, such as dam height and spillway size, are normally dictated by reservoir routing performed under design flood conditions, use of precise statistical information on governing hydrologic variables is of utmost importance in view of safety and economy. In this study, variations in hydrologic parameters that are utilized in reservoir flood routing are discussed in a practical application with a flood detention dam. Furthermore, probability density functions and coefficients of variation of selected random parameters involved in routing computations are investigated. Within the scope of this study, statistical parameters of inflow, outflow, and reservoir water level are investigated through Monte Carlo analysis. Additionally, a sensitivity analysis is conducted to assess the effects of possible variations in associated uncertainties of hydrologic parameters.*

***Key Words:*** *Hydrology, Uncertainty, Reservoir Routing, Monte Carlo Analysis*

## Introduction

Heavy precipitation or snowmelt results in high flow conditions, during which flooding may occur if the stream capacity is not enough to carry the resulting runoff. Rainfall normally produces the highest peak flows, whereas the combination of rainfall and showmelt yields largest flood volumes (Yanmaz, 2006). One of the leading factors causing pronounced flooding problems is urbanization, which results in significant changes in land use. Since runoff is directly related to percent urbanization, risk of occurrence of high runoff volumes, which may cause serious flooding problems, increase in highly urbanized areas. In addition to urbanization, other factors, such as effects of climate change also increase the chance of flooding and its consequences (Borrows, 2006). Many forms of structural and non-structural flood-defense systems were developed to mitigate negative impacts of floods. Nevertheless, flooding is still the most damaging of all natural disasters. One-third of the annual natural disasters and economic losses and more than half of all fatalities are flood-related (Douben, 2006). The worldwide damage caused by floods has been extremely severe in recent decades. No other natural hazard has appeared so frequently, threatened more human lives, generated such large economic losses, ruined more fertile land, and destroyed more houses (Douben, 2006). In economic terms too, floods were responsible for about one third of the overall losses between 1986 and 1995 (Loster, 1999; Munich-Re, 1997).

Coping with floods has been remained as an important issue in applied hydrology and hydraulics. Traditionally, flood mitigation measures were developed based on deterministic analysis. However, recently, significance of associated uncertainties has been realized and research is more focused on risk and reliability based approaches. Apel et al. (2004) state that flood disaster mitigation strategies should be based on a comprehensive assessment of the flood risk combined with a through investigation of the uncertainties associated with the risk assessment procedure. Because of random processes, reliability modeling and other probabilistic techniques are becoming increasingly important tools in hydraulic modeling and decision making (Johnson, 1996). Impacts of associated uncertainties of hydrologic and hydraulic parameters on design and operation of water resources systems have been investigated by various researchers. Such analyses are usually conducted in terms of risk and reliability associated with hydraulic structures. A brief review of recent literature on this topic is provided below.

Johnson (1992) and Johnson and Ayyub (1992) investigated the reliability of bridge scour estimates. Johnson (1992) developed a relationship between safety factors and the probability of bridge failure due to pier scour. Johnson and Ayyub (1992) determined the time-dependent probability of failure due to scour around a bridge pier. In both of these studies, it is stated that the results of the analysis are dependent on the underlying assumptions of uncertainty. Zhao et al. (1997) utilized linearly-constrained Monte Carlo simulation with the unit hydrograph theory and routing techniques to evaluate the reliability of hydraulic structures. As an example, the proposed methodology is applied to evaluate the overtopping risk of a hypothetical flood detention reservoir downstream of Tong-Tou watershed in Taiwan. Bowles et al. (1999) conducted a demonstration risk assessment for Alamo Dam. The existing dam and 19 structural risk reduction alternatives were evaluated for flood, earthquake, and normal operating conditions. As a conclusion, it is stated that risk assessment appeared to be a natural and holistic approach that should lead to a better dam safety evaluation and design. Yanmaz (2000) performed a dynamic reliability analysis for a diversion facility. The dynamic reliability model is based on resistance-loading methodology with random independent loading having a Poisson process and random fixed resistance. The relationship between the total cost of the diversion facility, its reliability, safety, and duration of construction are examined in a decision-making framework. Yanmaz and Cicekdag (2001) developed a composite reliability model for the reliability assessment of bridge pier scour using static resistance-loading interference. Use of the model is illustrated in a practical application in which a relationship is obtained between the reliability and safety factors under various return periods. Kuo et al. (2007) conducted a risk analysis for overtopping event of Feitsui Reservoir. In this study, they stated that there were many uncertain factors that could affect dam overtopping risk. They also pointed out that various uncertainty analysis methods were available to propagate the associated uncertainties into resulting risk and reliability values. They utilized five different methods - Rosenblueth's point estimation method, Harr's point estimation method, Monte Carlo simulation, Latin hypercube sampling, and the mean-value first-order second-moment method - for assessing overtopping risk of Feitsui Reservoir. Natale and Savi (2007) investigated inundation of Rome by Tibet River. Rainfall, rainfall-runoff, river flood propagation, and street flooding processes are simulated in detail to produce the inundation scenarios analyzed by Monte Carlo method. The study showed that severe floods having a return period greater than 180 years overtop both the left and right river banks and inundate the northern outskirts of Rome.

Contrary to the aforementioned investigations, the number of studies dealing with probabilistic reservoir routing are limited. Yanmaz and Gunindi (2006) conducted reservoir routing studies in which they treated certain hydrologic parameters as random variables. In that study, they used Monte Carlo simulation technique. They studied Fol Creek Basin as a pilot study area. The basin, located in Eastern Black Sea region of Turkey, is subject to frequent floods leading to loss of several lives and considerable damage to all kinds of facilities (Yanmaz and Coskun, 1995; Yanmaz and Gunindi, 2006). Yanmaz and Gunindi (2006) proposed a flood detention dam to mitigate floods. They concluded that the effect of initial water level in the reservoir, the coefficient of variation and the probability density function (PDF) assigned to water stage, and various dimensions of the dam on the overtopping reliability may be topics for further study. The present study will mainly focus on the investigation of these topics.

In addition to uncertainties in initial water level in the reservoir, uncertainties associated with various other hydrologic parameters may impact reservoir routing. In this study, runoff coefficient used in mathematical representation of inflow hydrograph ($C$), rainfall intensity ($i$), size of drainage area ($A$), and time to peak of the inflow hydrograph ($t_p$) are modeled as random variables and routing for a hypothetical reservoir is conducted. Monte Carlo analysis has been widely used in uncertainty modeling because of its robust character (Kwon and Moon, 2006). This technique will be used in this study to propagate the impact of random input variables on the instantaneous water surface elevation in the reservoir. Temporal variation in reservoir water level will be investigated for various configurations of statistical properties. To this end, various probability density functions (PDFs) and coefficient of variations (COVs) are assigned to the random variables and the temporal change in reservoir water level and outflow are analyzed.

## Reservoir Routing

Reservoir routing is normally performed for both design and analysis purposes. When the inflow hydrograph is known, the outflow rate can be determined by using reservoir routing. In this study, reservoir routing will be carried out using a numerical solution. The continuity equation is given below:

$$\frac{dS}{dt} = I(t) - Q(h) \tag{1}$$

where *S* is storage, *t* is time, *I(t)* and *Q(h)* are inflow and outflow, respectively. Since *S* and *Q(h)* are both unknown, another equation is needed to solve for the change in outflow with time. Differential storage in the reservoir, *dS* can be expressed by *dS=A(h)dh*, where *A(h)* is the surface area of the reservoir at an elevation *h* which is measured from the axis of bottom outlet and *dh* is the differential depth. Using elevation-area-volume relationship of the reservoir, *A(h)* can be represented mathematically. On the other hand, the outflow can be expressed as a function of *h* by using the appropriate equations for bottom outlet or overflow spillway, which are derived from the conservation of energy principle. Therefore, Equation (1) becomes:

$$\frac{dh}{dt} = \frac{I(t) - Q(h)}{A(h)} = f(h,t) \tag{2}$$

where *dh/dt* is the rate of change of water surface elevation. When all the expressions forming Equation (2) are expressed mathematically, the temporal variation of the reservoir water level and hence the outflow can be obtained. In ungauged basins, however, the inflow hydrograph cannot be obtained. In such cases, the inflow hydrograph proposed by Horn (1987) can be used. This hydrograph was obtained by fitting the dimensionless unit hydrograph of U.S. Conservation Service (Chow et at., 1988) in the general form of a Pearson type 3 PDF as shown below:

$$I(t) = I_p \left(\frac{t}{t_p}\right)^{3.5} \exp\left(-3.5\left(\frac{t}{t_p} - 1\right)\right) \tag{3}$$

where $I_p$ is the peak inflow and $t_p$ is the time to peak of the inflow hydrograph. The value of $I_p$ can be calculated by the rational method for small catchments:

$$I_p = CiA \tag{4}$$

For a flood detention dam with dual-outlet, flow takes place through the bottom outlet when water surface elevation is smaller than the crest elevation of the overflow spillway and through both the bottom outlet and the spillway when water surface elevation exceeds the crest elevation of the overflow spillway. Outflow from the bottom outlet and overflow spillway can be mathematically represented by using conservation of energy and other related hydraulic equations. When equations for *I(t), Q(h)*, and *A(h)* are inserted into Equation (2), a first order non-linear ordinary differential equation is obtained. This ordinary differential equation can be solved by Euler method because of its simplicity. The water surface elevation, $h_{n+1}$, at time $t_n + \Delta t$ can be computed from:

$$h_{n+1} \cong h_n + \Delta t \times f(t_n, h_n) \tag{5}$$

where $h_n$ is the water surface elevation at time level $t_n$ and $\Delta t$ is the computational time interval.

## Uncertainty analysis

In the analysis of the problem, a hypothetical flood detention basin is considered with the following equations for *I(t)*, *Q(h)*, and *A(h)*:

$$I(t) = CiA\left[\left(\frac{t}{t_p}\right)^{3.5} \exp\left(-3.5\left(\frac{t}{t_p} - 1\right)\right)\right] \tag{6}$$

$$Q(h) = \begin{cases} 0.0 & h \le K \\ 1.873h^{0.5} & K < h < h_s \\ -2.98h^3 + 106.8h^2 - 1100h + 3490 & h \ge h_s \end{cases} \tag{7}$$

$$A(h) = 25h^3 - 120h^2 + 5600h \tag{8}$$

where $K$ and $h_s$ are the entrance elevation of the riser pipe and crest elevation of the spillway, respectively. In this study, the initial water level ($h_0$), the runoff coefficient ($C$), the rainfall intensity ($i$), the size of the drainage area ($A$), and the time to peak of the inflow hydrograph ($t_p$) are modeled as random variables. The goal in this study is to calculate the PDF for the water surface elevation, $h_{t_f}$ at a desired future time, $t_f$. Throughout the course of this study, two different MC analyses are conducted. The first version, which will be referred to as "MC-without sampling in intermediate steps (MC-1)" uses the following procedure:

Step 0. Set total number of MC iterations, $N$.
Step 1. Set time to stop, $t_f$.
Step 2. Assign PDFs for $h_0$, $C$, $i$, $A$, and $t_p$.
Step 3. Sample representative values for $h_0$, $C$, $i$, $A$, and $t_p$ from their associated PDFs.
Step 4. Using sampled values for $h_0$, $C$, $i$, $A$, and $t_p$ calculate $h_{t_f}$ using Equation (6).
Step 5. If total number of MC iterations is not reached go to Step 3, otherwise stop.

In this version of MC analysis, sampling is only done at $t_0$ and routing is carried out until $t_f$ is reached. In other words, no sampling is performed in the intermediate time steps. Uncertainty associated with this solution algorithm is neglected. At $t_0$, values of random parameters i.e., $h_0$, $C$, $i$, $A$, and $t_p$ are set and the rest of the procedure is carried out in a deterministic manner. A second version of MC analysis which will be referred to as "MC- with sampling (MC-2)" is also conducted to calculate PDF of $h_{t_f}$. The procedure for this version is as follows:

Step 0. Set total number of MC iterations, $N$.
Step 1. Set time to stop, $t_f$.
Step 2. Assign PDFs for $h_0$, $C$, $i$, $A$, and $t_p$.
Step 3. Sample $N$ representative values for each one of the random variables $h_0$, $C$, $i$, $A$, and $t_p$ from their associated PDFs.
Step 4. Using $N$ sampled values for $h_0$, $C$, $i$, $A$, and $t_p$, calculate $N$ different $h_{t+i\Delta t}$ values by using Equation (6); $i=1, 2,\ldots, k$ where $t + (k+1)\Delta t = t_f$.
Step 5. Generate frequency distribution for $h_{t+i\Delta t}$.
Step 6. If $t_f$ is reached, stop. If $t_f$ is not reached, sample $N$ representative values for each one of the uncertain parameters $C$, $i$, $A$, and $t_p$ from their associated PDFs and sample $N$ representative values for $h_{t+i\Delta t}$ from its frequency distribution.
Step 7. Using $N$ sampled values for $h_{t+i\Delta t}$, $C$, $i$, $A$, and $t_p$ calculate corresponding $N$ for $h_{t+j\Delta t}$ by using Equation (6); $j=2, 3,\ldots, k+1$.
Step 8. Go to Step 6.

In this version of MC analysis, for the first time step, sampling from the associated PDF of each random input variable and for the rest of the time steps sampling from the associated PDFs of $C$, $i$, $A$, and $t_p$ and sampling from frequency distribution of $h_{t+i\Delta t}$ is conducted.

## Results and Discussion

First, in order to compare the results of two different versions of MC analysis, the same set of inputs are used and the probability density functions for $h_{t_f}$ are calculated for various $t_f$ values. Characteristics of the input variables are summarized in Table 1 in which $\mu$ and COV are the mean and coefficient of variation, respectively. Limited information is available in the literature concerning the magnitudes of COVs and types of PDFs to be assigned to random hydrologic and hydraulic variables. The order of magnitudes and types of PDFs of the governing variables are selected with reference to Johnson (1996), Yanmaz (2000), Yanmaz and Cicekdag (2001), and Beser (2005). In Monte Carlo analysis, number of runs affects the reliability of results. Yanmaz and Gunindi (2006) determined change in the coefficient of variation of reliability with respect to number of simulations and concluded that 20,000 runs is sufficient in a similar analysis. Therefore, in this study 20,000 MC runs are utilized for all types of analysis. Probability density functions of water surface elevations at the end of 10, 100 and 250 minutes with the input parameters given in Table 1 for two different versions of MC analysis are given in Figure 1.

**Table 1.** Inputs for MC Analysis

| Variable | Nature | Type of PDF | $\mu$ | COV |
|---|---|---|---|---|
| *K (m)* | Deterministic | - | 2.0 | - |
| $h_s$ *(m)* | Deterministic | - | 8.0 | - |
| $h_0$ (m) | Random | Normal distribution | 5.0 | 0.2 |
| *C* (-) | Random | Normal distribution | 0.6 | 0.3 |
| *i* (mm/hr) | Random | Normal distribution | 85.68 | 0.1 |
| *A* (km$^2$) | Random | Normal distribution | 7 | 0.1 |
| $t_p$ (hr) | Random | Normal distribution | 1 | 0.2 |

In order to investigate impact of utilizing different PDFs for random input variables i.e., $h_0$, *C, i, A,* and $t_p$, uniform distributions are utilized instead of normal distributions. Characteristics of input variables for this case are given in Table 2. Probability density functions of water surface elevations at the end of 10, 100, and 250 minutes with the input variables given in Table 2 for two different versions of MC analysis are given in Figure 2. In Figures 1 and 2, *n* represents the frequency. As can be seen from Figures 1 and 2, although the PDFs for water surface elevations at various times differ for different input variable combinations (i.e., normal and uniform PDFs are assigned to input variables for results given in Figures 1 and 2, respectively) the mean water surface elevation values are close to each other. Changes in mean water surface elevation with time for both input variable combinations are given in Figure 3.

**Table 2.** Inputs for MC Analysis

| Variable | Nature | Type of PDF | Range |
|---|---|---|---|
| *K (m)* | Deterministic | - | 2.0 |
| $h_s$ *(m)* | Deterministic | - | 8.0 |
| $h_0$ (m) | Random | Uniform distribution | 2.0-8.0 |
| *C* (-) | Random | Uniform distribution | 0.06-1.14 |
| *i* (mm/hr) | Random | Uniform distribution | 59.98-111.38 |
| *A* (km$^2$) | Random | Uniform distribution | 4.9-9.1 |
| $t_p$ (hr) | Random | Uniform distribution | 1440-5760 |

Percent discrepancy in mean water surface elevations with respect to discrete results is calculated as follows:

$$discrepancy = \frac{|dicrete\,result - mean\,value|}{dicrete\,result} * 100 \quad (9)$$

Discrete result is the water surface elevation calculated by using discrete values (i.e., mean values corresponding to normal PDFs of the input variables) for all the input variables. In other words, no Monte Carlo sampling is conducted, but Euler's formula is utilized with crisp input values in order to calculate discrete results.

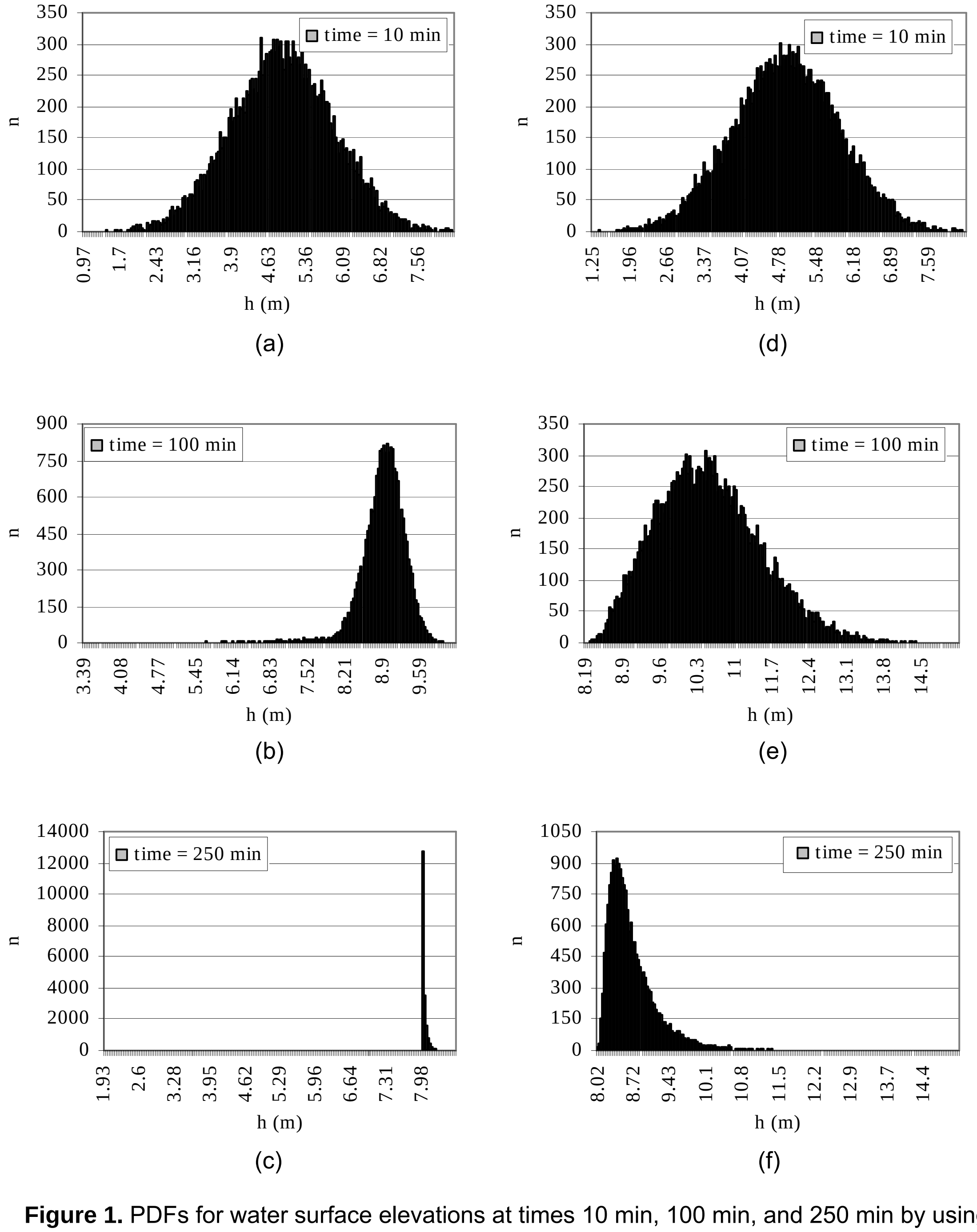


**Figure 1.** PDFs for water surface elevations at times 10 min, 100 min, and 250 min by using MC-1 ((a), (b), and (c)) and MC-2 ((d), (e), and (f)).

Percent discrepancies for both normal and uniform PDFs for input variables are given in Figure 4. As can be seen from Figure 4, the highest percent discrepancy (i.e., 11%) occurs for MC-1 when PDFs of input variables are chosen as uniform. MC-2 results, when normal PDFs are used for input variables, best mimic discrete results. In other words, discrepancies associated with this case are minimal. The maximum discrepancy in mean surface elevations relative to discrete results occurs around 70 minutes for all cases other than MC-2 when PDFs of input variables are normal. At times 50 and 60 minutes, discrete water surface elevations are 7.43 m and 8.62 m, respectively.

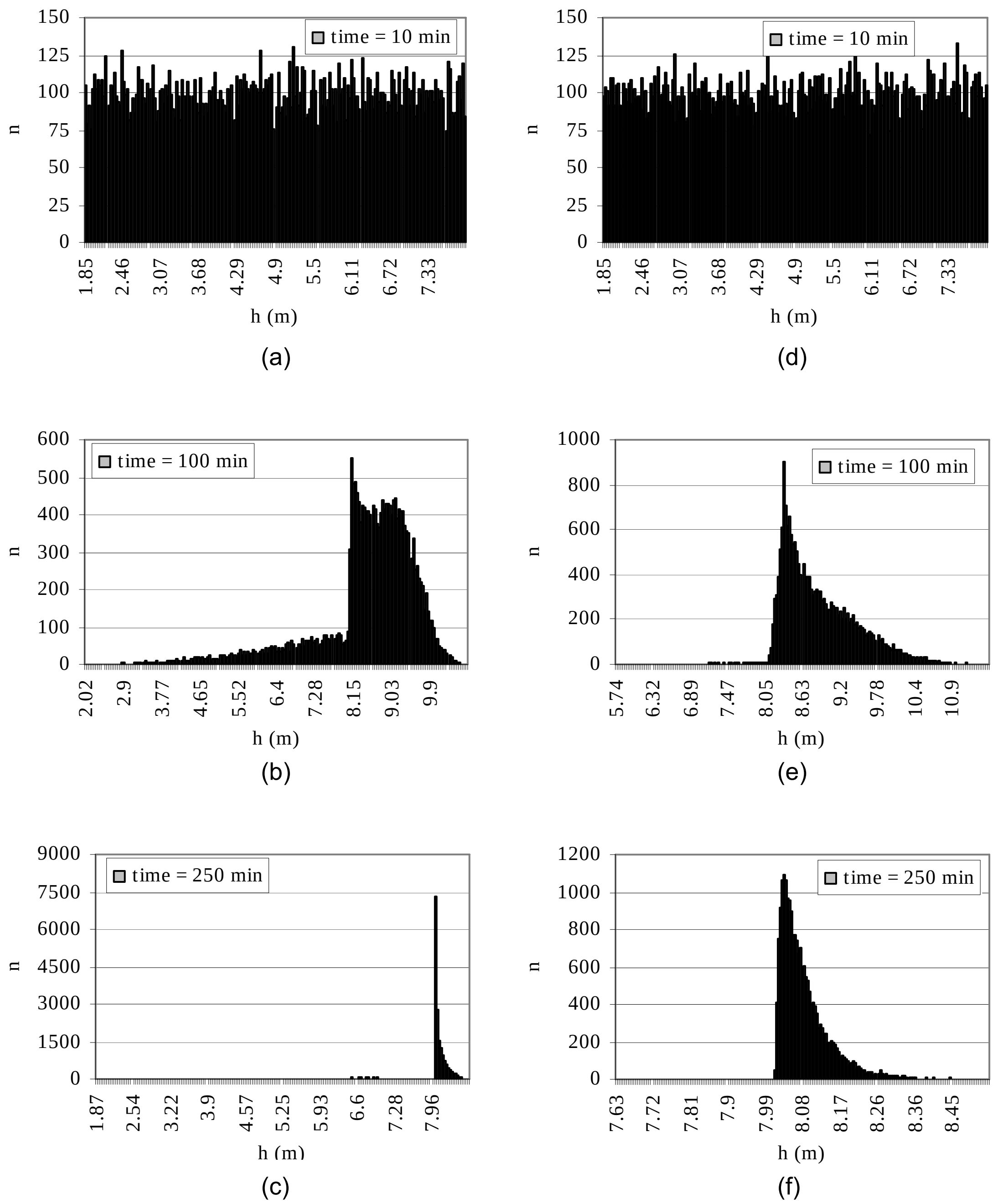


**Figure 2.** PDFs for water surface elevations at times 10 min, 100 min, and 250 mins by using MC-1 ((a), (b), and (c)) and MC- 2 ((d), (e), and (f))

The overflow spillway height is chosen as 8 m for the reservoir. According to discrete results, sometime between 50 and 60 minutes, the overflow spillway starts discharging water in addition to the bottom outlet. Since calculations are carried out for a time interval of 10 minutes, for the discrete case water surface elevation at time 70 min is calculated by considering discharges from both bottom outlet and overflow spillway. However, when Monte Carlo analysis is conducted, among 20,000 runs a number of them do not result in water surface elevations above 8 m at time 60 min and associated discharges are calculated only considering the bottom outlet. It may be the cause of high percent discrepancies around t=70 minutes.

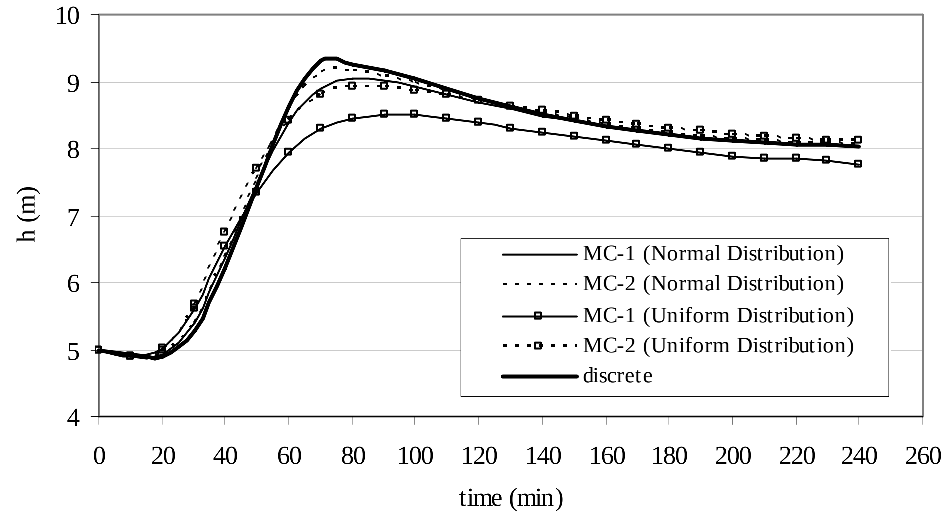


**Figure 3.** Changes in water surface elevation with time

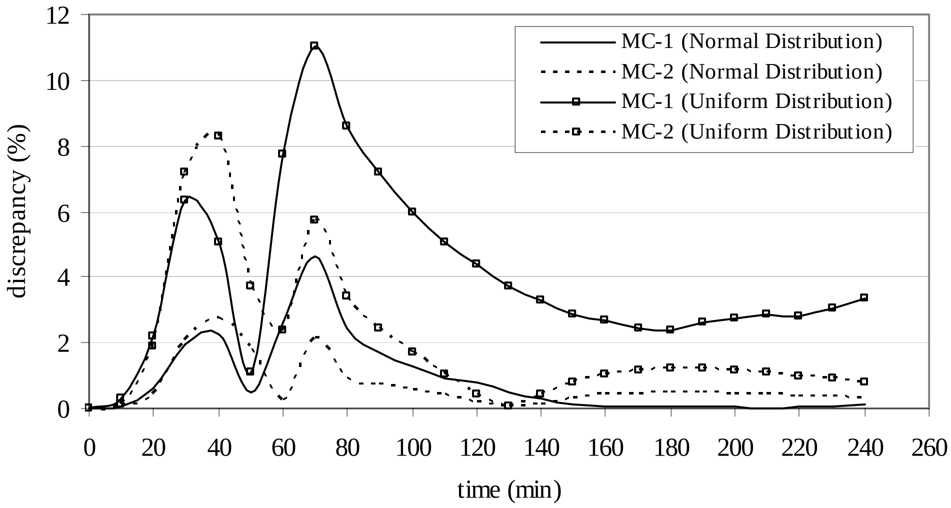


**Figure 4.** Percent discrepancies in mean water surface elevation with respect to discrete results

As a second sensitivity analysis, the impact of coefficients of variation on water surface elevation is investigated. This analysis is only performed for MC-2 when input variables have normal PDFs. In order to investigate the impact of degree of uncertainty on mean water surface elevation, all the COVs of input variables (see Table 1) are changed and Monte Carlo analysis is conducted for 3 different cases. The case which corresponds to the COVs given in Table 1 is named as “COV.” Then all the COVs are halfed and doubled and these cases are referred to as “0.5COV” and “2COV”, respectively. The results are given in Figure 5. In order to observe the impact of degree of uncertainty on the mean water surface elevation, discrete results are also plotted on the same figure. As expected, “0.5COV” case performs closest to the discrete results and as degree of uncertainty (i.e., COV) increases the difference between mean surface elevations and discrete results increase.

In the previous analysis, COVs of all the input variables are changed simultaneously. To find out uncertainty in which of the input variable have respectively more impact on the resulting uncertainty in the water surface elevation, a more detailed analysis is conducted. This analysis is only performed for MC-2 when input variables have normal PDFs case as well. Changes in water surface elevation with time for 5 different cases with doubling only the COVs of one of the random input variables are compared with the case in which COVs for all input variables are doubled simultaneously. The results are given in Figure 6. In this figure, the case in which COV of initial water level is doubled is marked as

"2COV_initial head." For this case, COVs of the rest of the random input variables (i.e., *C, i, A,* and $t_p$) are kept the same as given in Table 1. In other words, COVs of *C, i, A,* and $t_p$ are taken as 0.3, 0.1, 0.1, and 0.2, respectively, and COV of initial water level, $h_0$ is taken as 0.4. Other cases are named similarly. In order to represent the variations in results more clearly, only mean water surface elevation results in the time range of 50-100 minutes are given in Figure 6.

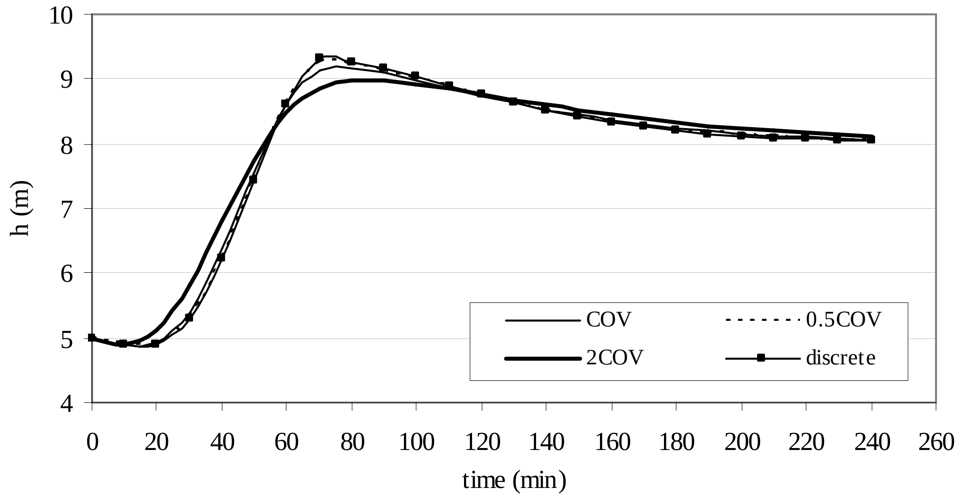


**Figure 5.** Change in water surface elevation with time for different COVs

As can be seen from Figure 6, uncertainty associated with time to peak has the greatest impact on the resulting uncertainty in the mean water surface elevation. Doubling the COVs of other input variables (i.e., $h_0$, *C, i,* and *A*) result in similar mean water surface elevations that are respectively far away from those generated by doubling all the COVs of the input variables simultaneously. Inspection of Figure 6 implies that doubling the COV of time to peak produces relatively close results with those generated by doubling all the COVs simultaneously.

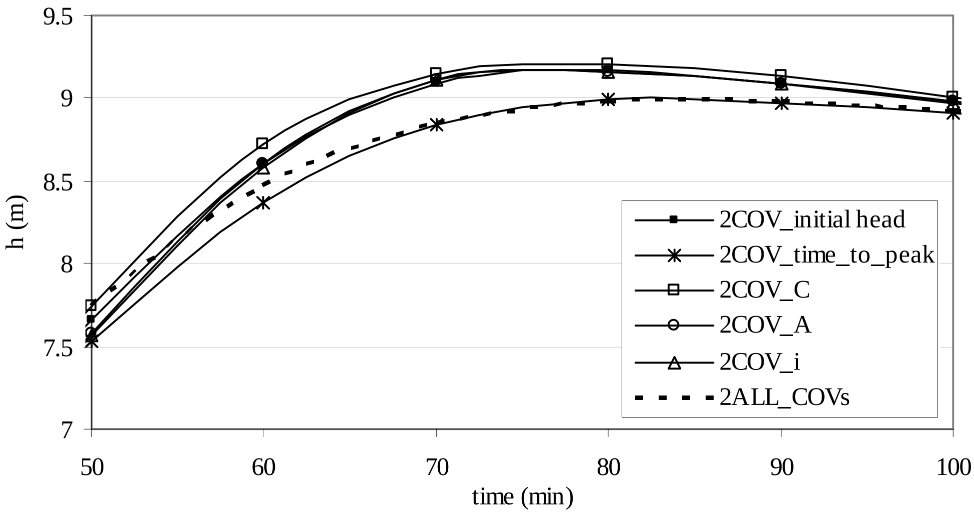


**Figure 6.** Impact of individual uncertainties in input variables on mean water surface elevation

## Conclusions

Uncertainties associated with various hydrologic parameters, such as runoff coefficient, rainfall intensity, size of drainage area, time to peak, in addition to the initial water level in a reservoir may impact resulting water surface elevation in the reservoir at a future time. In order to obtain a realistic water surface elevation estimate at a desired future time, uncertainties associated with the input variables need to be included in the reservoir routing analysis. In this study, Monte Carlo analysis is used to propagate uncertainties in input variables into temporal water surface elevations. Two different versions of MC analysis are used. As can be seen from the results (Figures 1 and 2) MC-1 results in a wider range of water surface elevations compared to those of MC-2. This is due to the fact that in MC-2, sampling from associated PDFs and frequency distributions are conducted at each time step which causes the chance of sampling of the extreme values to decrease. Therefore, the water surface elevations generated as the result of MC sampling at each progressing time step tend to gather in a narrower band within the vicinity of the mean value. We believe that the MC-1 produces more realistic results which represent all the possibilities. In this study, we also investigated the impact of utilizing different PDFs for random input variables. Frequency distributions of the water surface elevation at the early time steps differ significantly; however, as time progresses both versions (input variable distributions are normal or uniform) generate similar results. As a final analysis, the impact of degree of uncertainties (i.e., COVs of normal PDFs) associated with each one of the random input variables on mean water surface elevation is investigated. As can be seen from Figure 6, uncertainty associated with time to peak has the most significant impact on the mean water surface elevation.

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