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Research Article

Risk-based Analysis of the Hydrological Uncertainties for Flood Management Strategies

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Abstract

Designing a hydraulic structure with high capacity can impose additional costs on the project. Therefore, the importance of accurate design and proper selection of design parameters, optimal determination of flood return period and proper capacity of the flow channel are some of the topics that should been considered. Risk-based flow hydrograph estimation allows designers to take into account the uncertainties of the decision process and increase the level of reliability of hydraulic structures. In this research, hydrological uncertainties have been formulated based on probabilities to estimate the hydrograph of the dam reservoir output. To achieve this goal, time series data of maximum annual instantaneous flow for a period of 45 years were collected and analyzed. To achieve this goal, the genetic algorithm optimization method was used to calculate the best response and optimum return period. The results showed that the 40-year return period is a suitable option due to the hydrological uncertainty. Flow routing showed that the peak of the output hydrograph in the reservoir with a volume of more than 45 million cubic meters (MCM) will create a difference of about 13 m^3/s.

Keywords: Genetic algorithm; Hydrologic uncertainty; Hydrograph; Risk-based analysis

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1. Introduction

Using the concept of uncertainty can provide part of the necessary reliability in the design of hydraulic structures. One of the most important factors that cause uncertainty in these structures are hydrological parameters such as flow rate and flood volume that may be subject to error (Van Gelder 2000; Xiao et al. 2009; Kong et al. 2018; Salas and Obeysekera 2019). Considering these uncertainties in the form of risk analysis and considering effective economic parameters will improve system performance. According to the mentioned concepts, hydrological risk analysis is a basic method of designing structures exposed to floods. Therefore, in case of access to the required information, risk analysis is considered as the most logical method of design flood selection. In risk analysis, economic and hydraulic parameters must be considered to calculate the return period of floods. Therefore, an optimal design based on risk analysis will create a balance between system costs and acceptable risk (Montanari and Grossi, 2008). Various methods of uncertainty have been used in previous studies. Fuzzy set theory provides a powerful tool for calculating ambiguities as well as considering the lack of sufficient knowledge about the components of a system in the modeling process. Probability models are another method of estimating uncertainty that has been used to predict hydrological events. But today it has been shown that hydrological phenomena such as precipitation, runoff, flood, and drought are random and multivariate and expressed by the characteristics of intensity, duration and magnitude (Rizwan et al. 2019). In terms of theory of probability distribution functions, there are different equations are known. The experimentally measured and recorded data are fitted with these theoretical distribution functions, and the best function that matches the data is selected as the probability distribution function, from which the value of the hydrological variable is given for each probability (Rahman and Bowling 2019).

Hydrological uncertainty is generally in the form of probabilistic models and leads to the production of quantities of variables with multi-year event estimates (Dehghani et al. 2019). Hence, numerous examples of the application of probabilities in phenomena related to water research topics can be traced in the last two decades. For example, probabilistic modeling to take into account hydraulic conduction uncertainty in groundwater resources, flow uncertainty analysis in estimating the average weight of flood damage and investigation of rainfall uncertainty in the design of urban runoff control system has been studied (Karamouz et al. 2018). Existing risk-based methods for minimizing flood damage prediction may not be appropriate in a time-varying environment. Conditional Risk Value (CVaRα) as the modified form of Valuable Risk Value (VaRα), considers the size and probability. Zhang et al. (2018) proposed a way for CVaRα to consider flood uncertainties and then infer the value of the conditional risk associated with flood risk over a given time horizon. The results showed that the proposed method can not only indicate the flood risk, but also be able to reflect the probability of the flood by selecting an appropriate level of confidence. Tung and Mays (1981) used Discrete Differential Dynamic Programming (DDDP) methods to design the flood control structure and to account for the hazards and hydrological and hydraulic uncertainties of the system using the uncertainty analysis methods.

Afshar et al. (2009) also optimized the overflow capacity by considering inherent uncertainties and hydrological parameters. Other methods of assessing the risk is the application of the Monte Carlo method, which in the research of Thompson et al. (1997) has been used by simulation of rainfall-runoff model. As presented in the previous studies, flood control is an important topic on water resource management and construction of the diversion tunnel could be a solution for the large surface reservoir.

However, the delivery capacity for the main channel to transport the diverted flow as a main concern for flood control has been investigated in this study.

Modeling flood characteristics such as peak flow, volume and duration are essential for planning and managing water resources in this regard that the inflow rate is considered to generate the inflow and outflow hydrographs under probabilistic framework.

2. Material and methods

2.1. Study area description

Huai River Basin is located in the east of China, which mainly consists of Huai and Yishusi River system (Fig.1). The flood of Huai River system mainly comes from the upstream of Huai River, Huainan and Funiu mountains area. According to the relevant statistical information, there have been 28 times of floods and droughts disasters since 1974 in Huai River. Hongze Lake is the large lake in Huai River, which have storage function. Under the design conditions, the capacity of reservoir is about 12 billion cubic meters. Therefore, it is essential to control flood, resource utilization and ecological water. Transferring the flood water from Hongze Lake using a diversion tunnel is an advantage project for this area. This section describes how to describe and analyze the risk parameters of flood deflection system design in the form of probabilistic models and various optimization methods. Long-term hydrological information in an area should be collected and analyzed on a daily basis and used as the basis for the simulation model (Sedighizadeh et al. 2011). Fig. 2 indicates the flow regime for a 45 years from 1974 to 2019.

2.2. Intelligent hydrologic model

Risk analysis is a method of designing structures exposed to floods. Therefore, risk analysis is a logical solution if the required information is available.

$$R = 1 - \left(1 - \frac{1}{T}\right)^{t} \quad (1)$$

$$R = 1 - (1 - PF)^{t} \quad (2)$$

where, t = study period (year), PF = the event probability, T = return periods, R = risk. This process is generated and fitted by a probabilistic model and the return periods are calculated. Genetic algorithm was used to achieve the optimal research objectives. Genetic algorithm as an optimization method is considered as an effective way to increase the accuracy and speed of decision making in water engineering issues (Zhu et al. 2014; Lalehzari et al. 2016).

In this study, a genetic algorithm is used to search for the optimal values of decision variables arranged in the genes of a chromosome. In this study, the goodness-of-fit test was performed to select the best distribution function based on the maximum likelihood estimation method and the chi-square test was performed by developing the computer code of each function in MATLAB programming and optimization by genetic algorithm. Estimation of parameters in this method involves selecting estimates of parameters that produce the maximum probability of occurrence of observations.

For a distribution whose probability density function is f(x) and whose parameters are α_1, α_2, ..., α_k, the likelihood function is determined so that the probabilistic density function (PDF) of both observations in certain values of the parameters is proportional to the following equation

$$L(\alpha_1, \alpha_2, \dots, \alpha_k) = \prod_{i=1}^{n} f(X_i, \alpha_1, \alpha_2, \dots, \alpha_k) \qquad (3)$$

The values α_1, α_2, ..., α_k, which maximize the likelihood function, are solved by taking a partial differential relative to α1, α2, ..., αk and replacing these partial derivatives equal to zero by the following equation

$$\frac{\partial L(\alpha_1, \alpha_2, \dots, \alpha_k)}{\partial \alpha_i} \qquad (4)$$

In many cases it is better to use the logarithm of the likelihood function as the following equation for maximization.

$$\frac{\partial ln\, L(\alpha_1, \alpha_2, \dots, \alpha_k)}{\partial \alpha_i} = 0 \qquad (5)$$

2.3. Chi-square test

The randomness of the data, the independence of the samples, the large enough sample are the conditions for using the Chi-square test.
For the chi-square test, the expected frequencies must first be determined using the test distribution and the c^2 statistic calculated, then the critical value from the chi-square table with the desired error level and degree of freedom n-k-1 (n number classes and k are the estimated number of variables) obtained. The general Chi-square formula is presented as follows

$$c^2 = \sum \frac{(f_o - f_e)^2}{f_e} \qquad (6)$$

In the above relation, f_o is the observed frequency and f_e is the expected frequency.

Since the chi-square distribution is obtained from the normal distribution, if the variable x belongs to the normal population with mean μ and standard deviation σ and n random sample is selected from this population, then each member of the sample using the following equation become standard, the following distribution will be obtained with degree *n* freedom.

$$c^2 = {z_1}^2 + {z_2}^2 + \dots + {z_n}^2 \qquad (7)$$

The equation of chi-square distribution with degree of freedom k, mean k and variance 2k is as follows.

$$F(x) = \frac{1}{(k/2-1)} \frac{1}{2^{k/2}} x^{(k/2-1)} e^{-x/2} \qquad (8)$$

2.4. Flow simulation

The following equation shows the flow rate through the circular tunnel of a hydraulic structure (Fig.3).

$$q_c = \sqrt{2g} A (\frac{S_f}{H_f})^{\frac{1}{2}} \qquad (9)$$

$$S_f = H + L.S_0 - \frac{D}{2} \qquad (10)$$

$$H_f = 1 + K_e + \frac{2gn^2 L}{R^{4/3}} \qquad (11)$$

where, H = hydraulic head (m); S_f = energy line slope; D = height of the flow in tunnel (m); A is the cross section (m^2), L = length (m), K_e = the input coefficient, n = Manning roughness coefficient, R = the hydraulic radius (m) and S_0 is the longitudinal slope.

If the cross-section diameter is less than D, by calculating the cross-sectional area (A), wet premier (WP) and hydraulic radius (Rh) the flow through the tunnel will be obtained in semi-full state.

$$\theta = 2 * cos^{-1}(((D/2) - H)/(D/2)) \qquad (12)$$

$$A = 1/2 * (\theta - sin(\theta)) * (D/2)^2 \qquad (13)$$

$$W_P = (D/2) * \theta \qquad (14)$$

$$Rh = A/WP \qquad (15)$$

$$Q = 1/nMan * A * Rh^{(2/3)} * (So)^{0.5} \qquad (16)$$

3. Results and discussion

3.1. Selecting the distribution function

The results showed that the inverse Gaussian method is the best probabilistic function for flood discharge.

$$f(x) = \sqrt{\frac{\lambda}{2\pi(x-\gamma)^3}} exp\left(-\frac{\lambda(x-\gamma-\mu)^2}{2\mu^2(x-\gamma)}\right) \qquad (17)$$

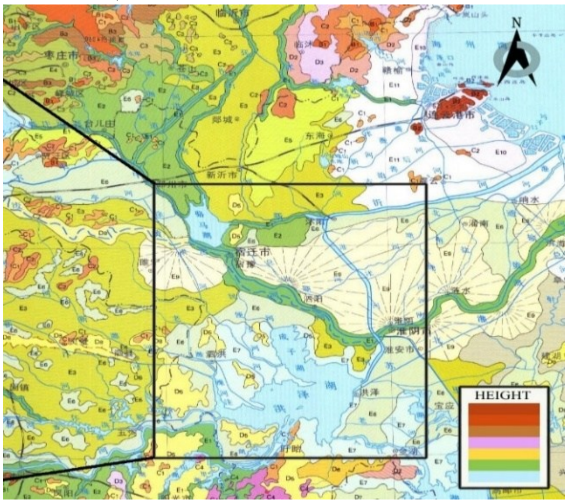

Figure 1. The Hongze Lake and Huai river system

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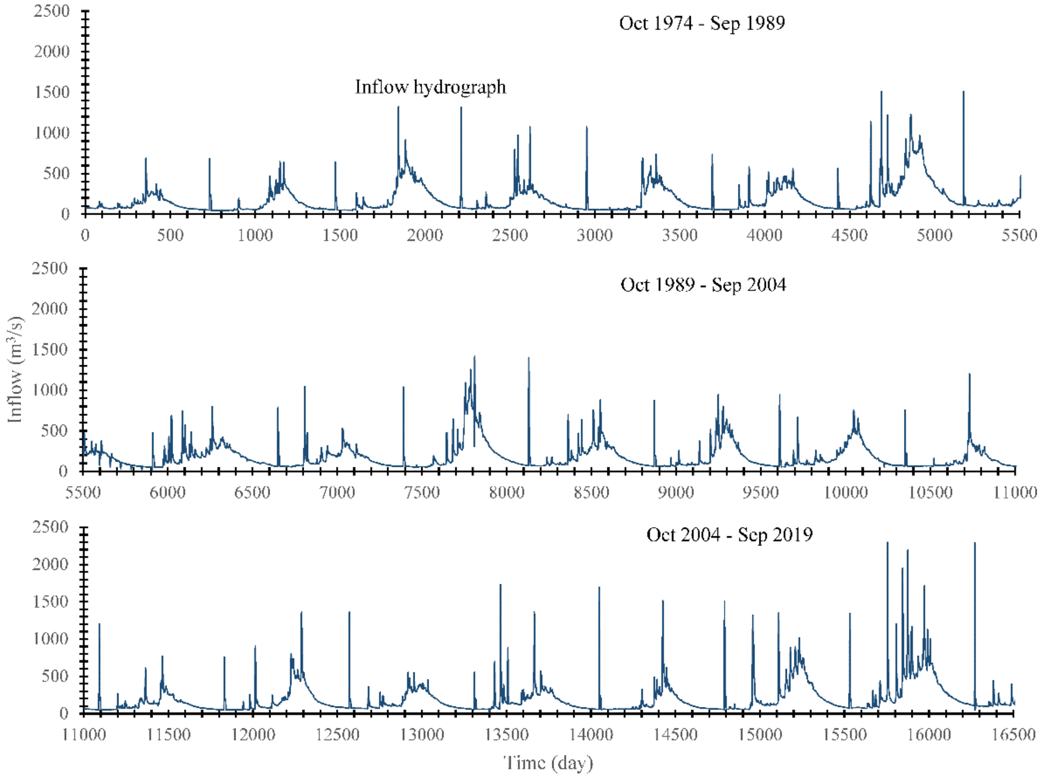

Figure 2. Inflow hydrographs in study area based on the daily long-term data

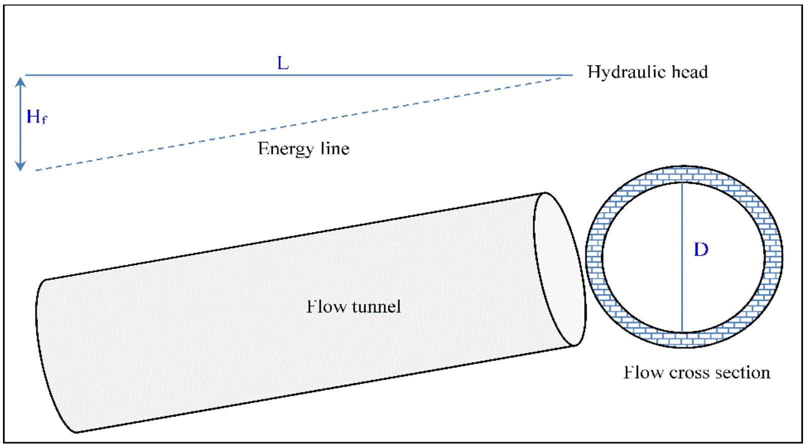

Figure 3. Schematic of the diversion tunnel

$$F(x) = \Phi\left(\sqrt{\frac{\lambda}{x-\gamma}}\left(\frac{x-\gamma}{\mu}-1\right)\right) + \Phi\left(-\sqrt{\frac{\lambda}{x-\gamma}}\left(\frac{x-\gamma}{\mu}+1\right)\right)\exp\left(\frac{2\lambda}{\mu}\right) \quad (18)$$

In above equations, f(x) is the probabilistic density function and F(x) is the cumulative distribution function. After selecting the model, the distribution parameters must be identified and a large number of new data can be reproduced by these parameters. The most important tests used for good fit are Chi-square and maximum likelihood error. Fig.4 shows the graphical comparison of the different frequency distribution function that the Inverse Gaussian was the suitable option. Optimization methods are incorporated to the problems to achieve this goal. Optimization methods are the techniques that can be used to achieve the desired result with minimal time and cost.

As the dimensions increase and the problems become more complex, the possibility of solving with conventional optimization methods or computational methods at the right time or with the available limited computational memory decreases and it becomes very difficult to achieve the optimal solution in these conditions.

One of the suitable solutions to solve such problems is a metaheuristic methods such as genetic algorithm that has been used in various researches (Haghighi and Zahedi 2014; Lalehzari and Kerachian 2020).

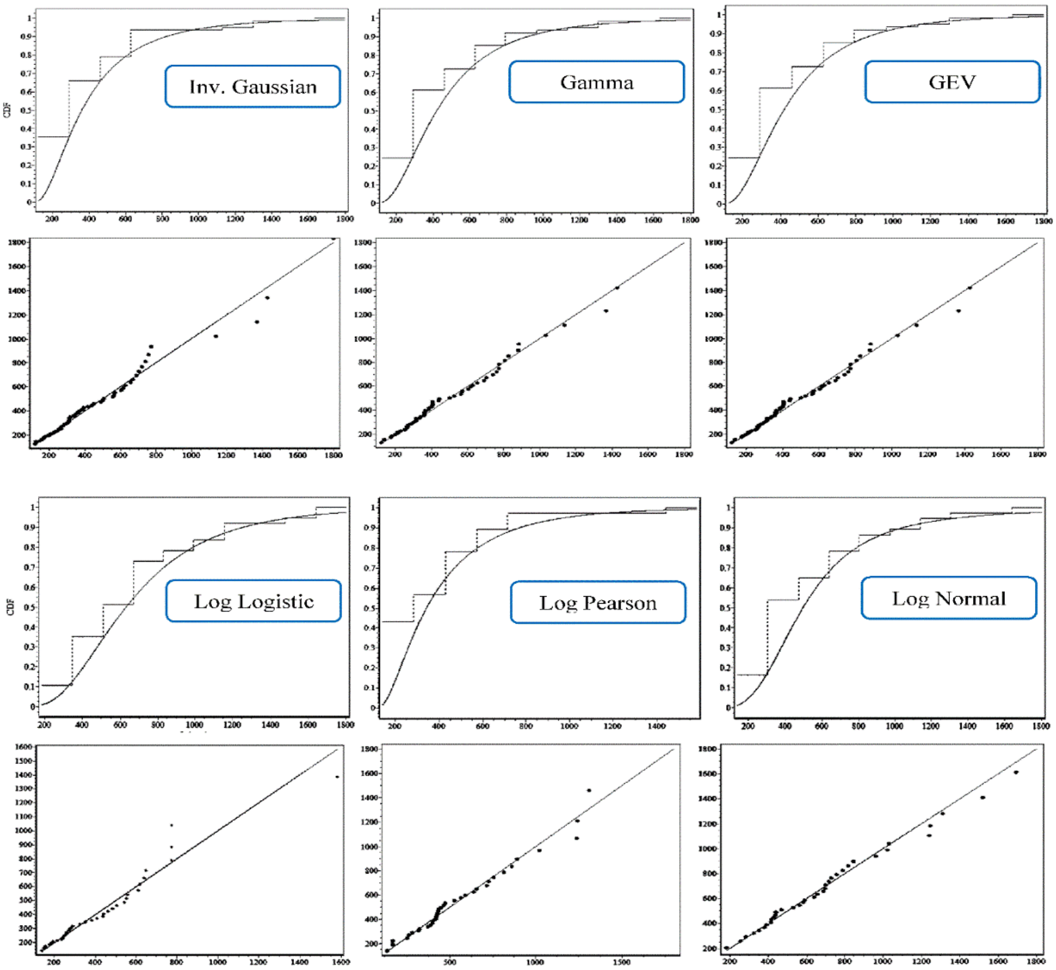

Figure 4. Graphical comparison of the distribution function

Table 1. Calibrated parameters using genetic algorithm

Distribution functions	α	β	k	λ	σ	μ	γ
Inv. Gaussian	-	-	-	1496	-	1834.1	34.76
Gamma	3.42	364.6	-	-	-	-	245.5
GEV	-	-	0.395	-	253.6	231.1	-
Log-Logistic	2.645	343.5	-	-	-	-	189.5
Log-Pearson	423.2	0.013	-	-	-	-	0.54
Lognormal	-	-	-	-	0.28	12.3	46.8
Normal	-	-	-	-	845.3	232.9	-
Weibull	1.8	545.8	-	-	-	-	34.5

Table 2. Comparing the distribution functions for probabilistic estimation

No.	Distribution function	Chi-square	Classification
1	Inv. Gaussian	0.113	
2	Gamma	0.124	
3	Gen. Extreme Value	0.243	
4	Log Logistic	0.643	
5	Log Pearson	0.843	
6	Lognormal	1.423	
7	Normal	1.428	
8	Weibull	1.823	
9	Gen. Pareto	2.152	
10	Logistic	3.458	

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Therefore, the selection of parameters was performed with the aim of minimizing the difference between the observed and estimated values of the flow using a genetic algorithm. Each distribution function has three parameters that were considered as decision variables in the optimization process. The numerical values of these parameters obtained in the calibration process and in multiple iterations of the optimization model are summarized in Table 1. Moreover, the objective function of the problem was the chi-square relationship, which its numerical values are shown in Table 2. Maximum likelihood estimation was also used to control the responses. According to the results obtained in this model, the Inverse Gaussian method has been the first choice for estimating the flow rate. Therefore, the selection of parameters was performed with the aim of minimizing the difference between the observed and estimated values of the flow using a genetic algorithm. Each distribution function has three parameters that were considered as decision variables in the optimization process. The numerical values of these parameters obtained in the calibration process and in multiple iterations of the optimization model are summarized in Table 1. Moreover, the objective function of the problem was the chi-square relationship, which its numerical values are shown in Table 2. Maximum likelihood estimation was also used to control the responses. According to the results obtained in this model, the Inverse Gaussian method has been the first choice for estimating the flow rate.

3.2. Flow routing

The inlet hydrograph to the reservoir must be transferred to the outflow system hydrograph in the calculations. Part of the flow is temporarily stored in the reservoir, which will cause the hydrograph peak. This process is called flood routing. Therefore, by preparing the reservoir water balance equation in a short time step, the following equation can be achieved.

$$\frac{I_t + I_{t+1}}{2} - \frac{O_t + O_{t+1}}{2} = \frac{S_{t+1} - S_t}{\Delta t} \tag{23}$$

Where I = inflow rate (m^3/s); O = outflow rate (m^3/s); S = storage capacity (m^3); t = time step number and Δt is the time interval (s). The inflow to the reservoir is determined according to the flood hydrograph in 2-hour time steps for this research (Fig.5). On the other hand, the volume of the reservoir at different heights can be estimated using the volume-height curve for the dam reservoir. Therefore, in the first step, by calculating the changes in flow transfer capacity from diversion tunnels at any height (and relative to each reservoir volume) to the right of the following equation, we can make unique curves for each proposed design for the system. Deviation in each iteration produced an optimization model. Examples of these curves are shown in Fig. 6. Therefore, the output flow in each time step can be simulated.

$$I_t + I_{t+1} + \left(\frac{2S_t}{\Delta t} - O_t\right) = \frac{2S_{t+1}}{\Delta t} + O_{t+1} \tag{24}$$

In large reservoirs, the peak point of the routed hydrograph is lower than the flow peak under normal conditions. Therefore, attention to flood routing affects the optimal design capacity (Rahman and Bowling 2019). The optimal capacity was determined through theoretical and economic analysis, taking into account the compensatory effects of existing resource capacity and water flow variability. The application of this method in a water transfer system showed that there is a balance between the proposed approach and the simulation approach based on reliability and the advantage of the proposed method is in simplicity, accuracy and computational efficiency. In addition, the effects of model parameters, demand uncertainty, input flow variability and the type of probability distribution on the optimal design of the water transmission system are discussed. The results showed that the proposed approach has been able to provide a theoretical basis for addressing the uncertainties in the design process of water transmission systems (Zhang et al. 2019). Fig. 7 indicates the inflow and outflow hydrographs obtained by flow routing process for different return periods. As shown in the figure, the uncertainty domain of each return period could be determined to estimate the confidence levels.

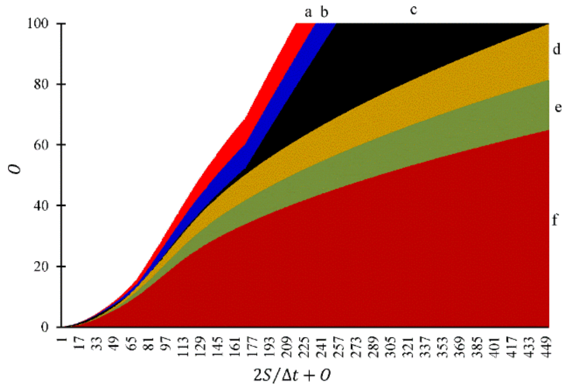

Figure 5. Non-dimensional ration of storage capacity and flow rate

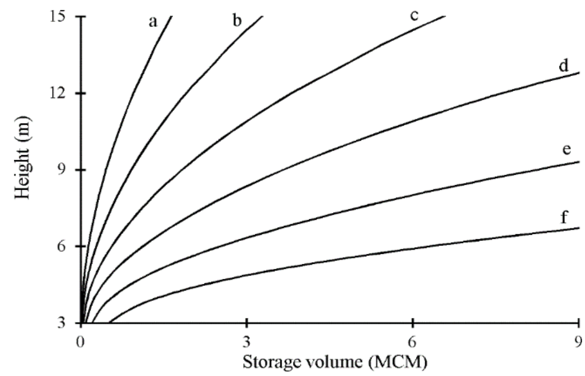

Figure 6. Curves of the non-dimensional form of the height – volume relationships

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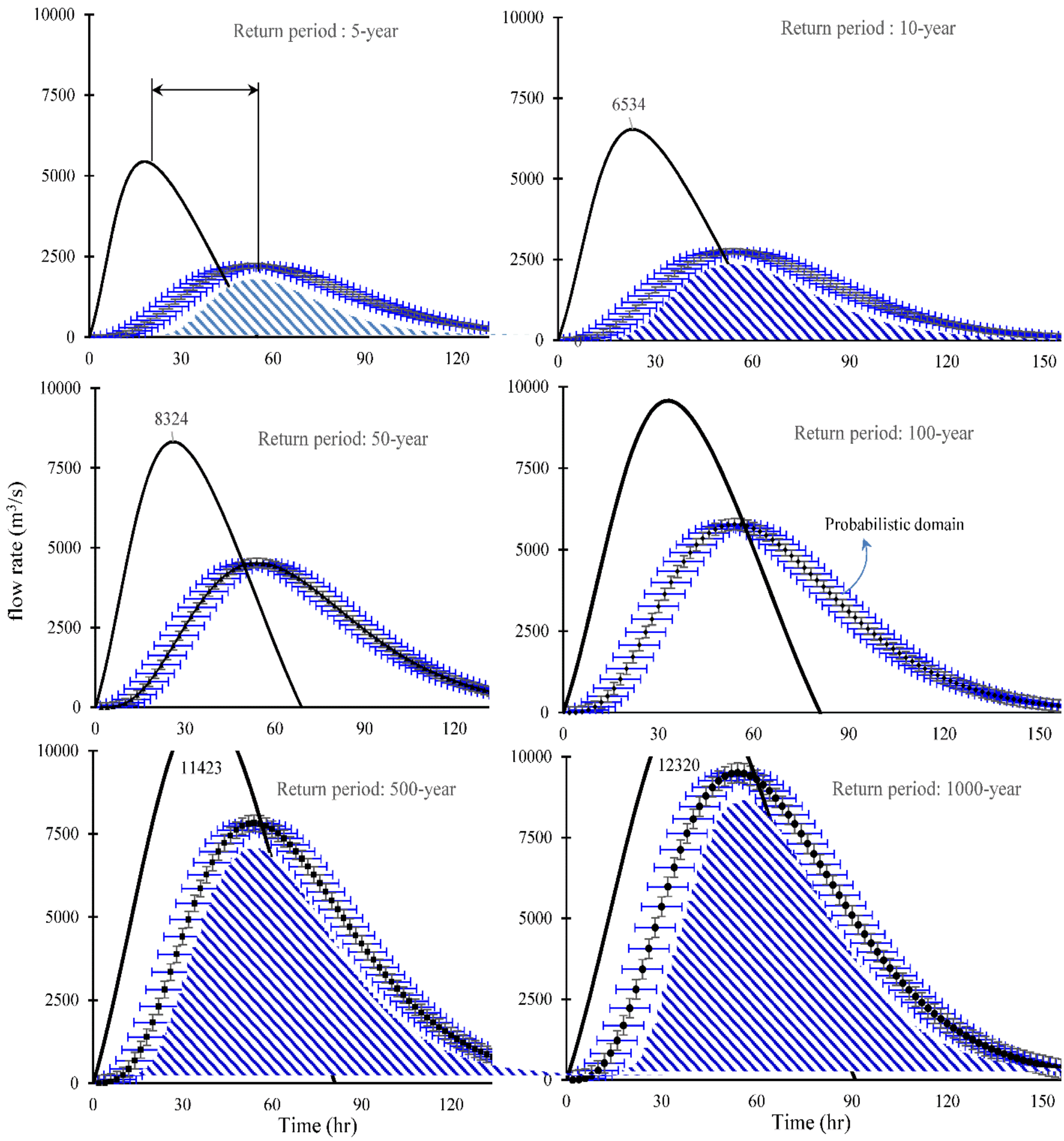

Figure 7. Flood roating in different return periods

4. Conclusion

Risk-based design is a method that allows the designer to apply the uncertainties in the project and present the results by calculating the reliability in the form of a probabilistic structure and analyze their risk. This method is undeniably important in engineering problems that have inherent errors due to environmental factors or accurate estimation of the input parameters of the problem is not available to designers. For this purpose, the univariate distribution functions were fitted to the flood discharge using the genetic algorithm method and the best obtained functions were used for frequency distribution. The return period of the flood peak was calculated and used to select the best return period. Therefore, the best functions fitted to the maximum annual instantaneous flow rate are Inverse Gaussian, Gamma, and Generalized Extreme Values, respectively, followed by functions such as Log Logistic and Log Pearson.

In general, the use of three-parameter functions can cover a large part of the prediction error and provide more accurate results. The application of an intelligent optimization algorithm in this research to calculate the coefficients of distribution functions showed that metaheuristic methods were more accurate than software calculations. In general, the results showed that the design of hydraulic structures based on the probabilistic model can evaluate the accuracy of the results and present the decision risk. Involvement of these models in the design can improve the economic conditions of the design.

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Authors Contribution
All the authors have participated sufficiently in the intellectual content, conception, and design of this work or the analysis and interpretation of the data (when applicable), as well as the writing of the manuscript.

Availability of data and materials
The data that support the findings of this study are available from the corresponding author upon reasonable. request.

Conflict of interest
The author states that there is no conflict of interest.

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