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MODELING OF RIVER FLOW FOR THE RESERVOIR ROUTING (CASE STUDY: HABLERUD RIVER - IRAN)

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ABSTRACT

Modeling of flow was made for Central Iran conditions on the example of river Hablerud where water reservoir is planning. Forms of dangerous flood hydrographs are very different because of different precipitation regimes. Practically it is impossible obtain typical design hydrograph for the reservoir routing. The storm precipitations and consequent floods can take place during any within-year interval, when water storage can be different with different probability. Therefore there is necessity to research a big amount of scenarios respecting possible combinations of flood hydrographs and water reservoir storages before floods for estimation of probability of damage. Observed hydrographs (30 years) can not represent base of all possible scenarios for reservoir routing of the requiring small probability. Consequently an aim of the represented research is modeling of long time series (1000 years) of daily discharges, which possesses a big variability but has approximately same statistic characteristics like observations. Method of Monte-Carlo according to fragment realization has been chosen among methods of stochastic simulation. At first annual discharge were simulated according to probabilistic curve, which was determined on the base of statistic parameters calculated with help of annual observed water discharges data. Then the simulated annual discharges were multiplied on ordinates of fragments. Every fragment was represented by 365 coefficients of observed daily water discharges of concrete year. Numbers of fragment was chosen by casual image. The choice of fragment was depended on value of annual discharge according to cluster analyses. The choice of algorithm of simulation was made on the base of comparison between month statistic parameters of the observed values and of the simulated values.

Key words: stochastic flood modeling, water reservoir, Hablerud River, Iran

INTRODUCTION

At present, most of the countries in the Middle East and North Africa are under water tension. Today, demand for water is on the rise everywhere in the world, particularly in arid and semiarid countries including Iran. Iran is one of the arid & semi-arid countries of the world with average precipitation of 251 mm/year [1,6]. The total renewable water resources of Iran is 130 Billion Cubic Meters (BCM), out of which 92% is used for agriculture, 6% for domestic use and services & 2% for industrial uses. About 70 % area of Iran suffer somehow from the lack of precipitation. Rapid population growth and low irrigation efficiency in agricultural sector have increased the demand for groundwater resources. The Hablerud River with the length of 117.3 km is located in the north of Iran and the east of Tehran.

Operation by the water reservoir must be provided the control flood. Therefore, the marked problems are very actually for safe water reservoir operation.

METHODS AND MATERIALS

At first, next statistical parameters of runoff were defined (according to observation 30-years): average annual runoff (\bar{Q}), coefficient variation (C_v), coefficient asymmetry (C_s) and coefficient autocorrelation (R_a). Same parameters were defined for the monthly values [1, 6]. Then, Monte-Carlo method was used for simulation of artificial rank [3, 5, 7]. 365 coefficients (K_{ij}) of observed daily water discharges of each concrete year were calculated:

$$K_{ij} = Q_{ij}/Q_i \quad \text{Eq. (1)}$$

Where: i - number of year and j - number of day during the year.

After that, all ensembles of coefficients K_{ij} were clustered respecting of values of annual runoff according to 3 groups water content:

- maximum (probability 0.1-25 %),
- mean (probability 25-75 %),
- minimum (probability 75-99 %).

So, all of fragments were made and every fragment had his number. Far, a long time rank of daily water discharges was simulated. At first probability of annual runoff was modeled according to homogeneous distribution random variables and was selected water content, then, conditional parameters of conditional probabilistic curve were defined. The ordinates of probabilistic curve were chosen from table of special gamma- distribution according to conditional coefficient variation (C_v^*)[4] which were calculated in depended on coefficient autocorrelation (R_a). The table of special gamma- distribution was selected in depended on ratio C_s/C_v . So, annual water discharges (Q_i) have been defined. Daily water discharges were defined in depended on fragment which was chosen according to simulating random number (i) with the help of homogeneous distribution random variables:

$$Q_{ij} = K_{ij} * Q_i \quad \text{Eq. (2)}$$

So, the artificial long time rank (1000 years) of daily water discharge has been obtained.

Verification of model

The represented algorithm of simulation was controlled with the help of comparison between observed and simulated data respecting of annual and monthly values: average runoff (\bar{Q}), coefficient variation (C_v), coefficient asymmetry (C_s) and coefficient autocorrelation (R_a). These differences were compared with relative standard errors (ε), which were calculated on the base of observed data ($n=30$ years) according to next formulas [4]:

$$\varepsilon_Q = \frac{C_v}{\sqrt{n}} * 100 \quad \text{Eq. (3)}$$

$$\varepsilon_{Cv} = \frac{1}{n+4Cv^2} \sqrt{\frac{n(1+Cv^2)}{2}} * 100 \quad \text{Eq. (4)}$$

$$\varepsilon_r = \frac{1-r^2}{\sqrt{n-1}} * 100 \quad \text{Eq. (5)}$$

$$\varepsilon_{Cs} = \frac{1}{C_s} \sqrt{\frac{6}{n} (1 + Cv^2)} * 100 \quad \text{Eq. (6)}$$

RESULTS

After calculating statistical parameters for observing and simulating data, summary results are represented in the tables (1-4).

Table 1. Comparison value \bar{Q} between the observed and simulated data

| Months & year | $\bar{Q}_{(observed)}$ | $\bar{Q}_{(model)}$ | $Error(\bar{Q}), \%$ | $(\Delta C_s / C_{s_{model}}) * 100$ |
|---------------|------------------------|---------------------|----------------------|--------------------------------------|
| year | 7.30 | 7.42 | 7.37 | 1.63 |
| Jan. | 6.79 | 7.17 | 4.32 | 5.32 |
| Feb. | 6.53 | 7.40 | 4.20 | 11.75 |
| Mar. | 8.31 | 9.75 | 5.89 | 14.73 |
| Apr. | 11.55 | 12.74 | 6.49 | 9.32 |
| May | 12.80 | 10.20 | 11.71 | 25.56 |
| Jun. | 7.45 | 5.75 | 12.71 | 29.50 |
| Jul. | 5.25 | 4.42 | 12.51 | 18.79 |
| Aug. | 4.21 | 3.85 | 10.78 | 9.24 |
| Sep. | 4.06 | 4.10 | 11.86 | 0.87 |
| Oct. | 5.72 | 6.55 | 9.28 | 12.64 |
| Nov. | 7.33 | 8.24 | 6.56 | 11.03 |
| Des. | 7.53 | 8.02 | 5.10 | 6.06 |

Table 2. Comparison value Cv between the observed and simulated data

| Months & year | $Cv_{(observed)}$ | $Cv_{(model)}$ | $Error(Cv), \%$ | $(\Delta Cv / Cv_{model}) * 100$ |
|---------------|-------------------|----------------|-----------------|----------------------------------|
| year | 0.4 | 0.4 | 13.63 | 0.39 |
| Jan. | 0.24 | 0.47 | 13.17 | 49.79 |
| Feb. | 0.23 | 0.46 | 13.15 | 49.8 |
| Mar. | 0.32 | 0.42 | 13.38 | 24 |
| Apr. | 0.36 | 0.48 | 13.47 | 26.14 |
| May | 0.64 | 0.6 | 14.54 | 7.69 |
| Jun. | 0.7 | 0.63 | 14.77 | 9.68 |
| Jul. | 0.69 | 0.59 | 14.73 | 16.07 |
| Aug. | 0.59 | 0.56 | 14.33 | 4.66 |
| Sep. | 0.65 | 0.42 | 14.57 | 53.47 |
| Oct. | 0.51 | 0.53 | 14 | 3.28 |
| Nov. | 0.36 | 0.5 | 13.49 | 28.58 |
| Des. | 0.28 | 0.48 | 13.27 | 41.72 |

Table 3. Comparison value R_a between the observed and simulated data

| Months & year | $r_{(observed)}$ | $r_{(model)}$ | $Error(r), \%$ | $(\Delta r/r_{model}) * 100$ |
|---------------|------------------|---------------|----------------|------------------------------|
| year | 0.41 | 0.43 | 15.48 | 4.67 |
| Jan. | 0.67 | 0.96 | 10.28 | 30.33 |
| Feb. | 0.69 | 0.83 | 9.75 | 17.32 |
| Mar. | 0.63 | 0.69 | 11.2 | 9.08 |
| Apr. | 0.81 | 0.74 | 6.39 | 9.03 |
| May | 0.91 | 0.91 | 3.26 | 0.1 |
| Jun. | 0.8 | 0.82 | 6.8 | 3.24 |
| Jul. | 0.78 | 0.67 | 7.24 | 15.85 |
| Aug. | 0.9 | 0.78 | 3.46 | 16 |
| Sep. | 0.91 | 0.59 | 3.36 | 53.36 |
| Oct. | 0.89 | 0.89 | 3.76 | 0.06 |
| Nov. | 0.9 | 0.94 | 3.46 | 3.54 |
| Des. | 0.88 | 0.98 | 4.35 | 10.58 |

Table 4. Comparison value Cs between the observed and simulated data

| Months & year | $Cs_{(observed)}$ | $Cs_{(model)}$ | $Error(Cs), \%$ | $(\Delta Cs/Cs_{model}) * 100$ |
|---------------|-------------------|----------------|-----------------|--------------------------------|
| year | 0.8 | 0.58 | 29.07 | 38.65 |
| Jan. | 0.48 | 0.86 | 44 | 44.27 |
| Feb. | 0.46 | 0.76 | 45.78 | 39.39 |
| Mar. | 0.65 | 0.62 | 33.97 | 5.15 |
| Apr. | 0.71 | 0.88 | 31.73 | 19.52 |
| May | 1.28 | 0.96 | 22.05 | 32.9 |
| Jun. | 1.39 | 1.23 | 21.36 | 12.56 |
| Jul. | 1.37 | 1.33 | 21.45 | 2.64 |
| Aug. | 1.18 | 1.02 | 22.86 | 15.77 |
| Sep. | 1.3 | 0.69 | 21.88 | 88.57 |
| Oct. | 1.02 | 1.05 | 24.67 | 2.8 |
| Nov. | 0.72 | 1.07 | 31.36 | 32.89 |
| Des. | 0.56 | 0.87 | 38.51 | 35.39 |

An analysis of the tables (1-4) is showing that relative differences between statistical parameters of observed and simulated ranks is very good respect to year values, but there are a significant differences respect to some months for some statistical parameters.

CONCLUSIONS

- 1- Differences of the annual statistical fragments between observed and model data are satisfactory and for the most of monthly intervals are satisfactory too. The errors are

significant for some months however, we can believe that observed rank is part of general totality of random values.

- 2- The considerable errors for some months may be explained by next main causes:
 - a little number of the taken clusters,
 - approximately ratio C_s/C_v .
- 3- Improvement of the model may be distinguished by confirmation clusters and ratio of C_s with the help of nonstandard method of definitions C_s [2].
- 4- Artificial simulated ranks of daily water discharges allow evaluate a significant amount of scenarios respecting of possible combinations of flood hydrographs and water reservoir storages before floods for estimation of damage probability.

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