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Sensitivity Analysis of River Flood Routing Model to Input Data

Ehsan Ranaee[1], Mohammad Mahmoodian[2] and Saeed Rahati[3]

***Abstract*—Our conclusive purpose of this research is to offer a procedure to study the sensitivity of flood routing models to the input discharge statistics of different hourly time steps. In some case studies, it could be obvious that after calibration of river flood routing modeling; some of the first output statistics in ascending branch of output hydrograph are not acceptable. This error occurs because of the influence of flood volume which has been passed the upstream boundary cross section before the chosen initial time step for modeling; consequently, it could not been utilized as the boundary conditions definition for flood routing modeling software. Other words, it could be noticed that time range of initial and boundary conditions is larger than modeling one. During an innovative procedure; we used MIKE11 software as an acceptable river flood routing model; and also, different structures of artificial neural networks (ANNs) to compute the sensitivity of river flood routing to the number of previous time steps discharge which are effective in modeling accuracy. In this way, we studied recorded flood discharge statistics during 30 years up to now in two hydrometric stations which are located in upstream and downstream of ZOSHK RIVER as our case study. Terminally, we recommended the best range of discharge time steps to use as the initial and boundary conditions of river flood routing modeling.**

***Index Terms*—Sensitivity Analysis, Flood Routing Modeling, MIKE11, Artificial Neural Networks (ANNs)**

I. Introduction

Flood routing bases on two partial differential equations which are named Dynamic Wave Equations (J.C.Borre de-Saint Venant, 1981) and contain Mass Continuity and Momentum Equations:

$$T\frac{\partial y}{\partial t} + A\frac{\partial v}{\partial x} + V\frac{\partial A}{\partial x} = 0 \qquad (1)$$

$$\frac{\partial v}{\partial t} + V\frac{\partial v}{\partial x} + g\frac{\partial y}{\partial x} = g(s_0 - s_f) \qquad (2)$$

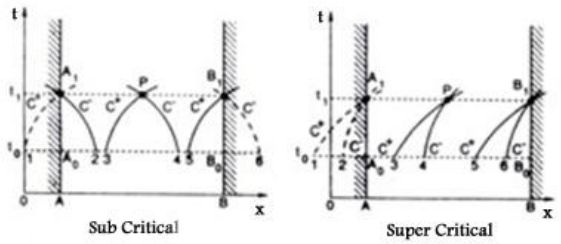

Fig. 1: Effective range of initial and boundary conditions in numerical modeling utilization.

Because of water viscosity property, flood movement in open channels occurs continually. Consequently, in each cross section through the channel, initial and boundary discharge conditions impress flood condition in next time steps. On the other hand, most of the numerical methods (finite difference and finite element methods) which are used to solve Dynamic Wave Equations for flood routing description contain schemes with two or three time steps (i-1, i, i+1). Furthermore, based on Courant Equation (R. Courant, K. Friedrichs and H. Lewy, 1928), there is some limitation in range of Δt and Δx definition. To wrap it up, it could be said that time range of input statistics definition; and also, sensitivity of each case study flood routing modeling to input discharge statistics have to be calculated.

During this research, after study and survey of schemes which are used in numerical methods in MIKE11 software structure, we analysed the sensitivity of model to hourly input discharge. Later on, according to aforesaid results we trained different structures of artificial neural networks; and finally, we tested the accuracy of both MIKE11 and ANNs models to the observed input discharge data. Our aim was achievement to accuracy of between 0.01 and 0.1 in output data in compare with observed ones. Needless to say that we choose this range as our desire accuracy, because of maximum and minimum acceptable accuracy in river engineering and structures design.

II. Methodology

A. MIKE11 Model

Implicit method as a numerical one with usage of Abbott and Lonescu schemes defines to sever Partial Differential Dynamic Wave Equations in MIKE11 software. As it can be clearly seen in figure.2, three time steps suppose to be effective in each step of output computation.

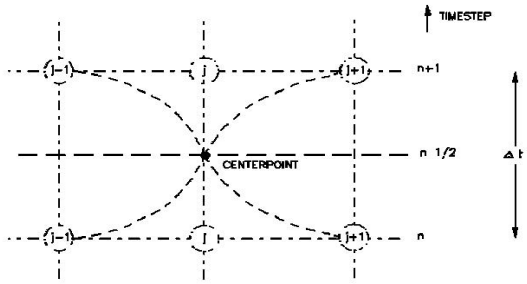

Fig. 2: Abbott and Lonescu schemes.

Commencing the project, we perused and analysed recorded time series of water level data in three hydrometric stations for 262800 hours, overall. ZOSHK, SARASIYAB-SHANDIZ and KANG stations are located in

[1] Islamic Azad University, Shoushtar branch, Young Researchers Club, Iran.
[2] Faculty of Civil Engineering, Chamran University, Ahvaz, Iran.
[3] Faculty of Electronic Engineering, Islamic Azad University, Mashhad branch, Iran.

upstream of the main branch, in downstream of the same branch and on the secondary branch; respectively. Using aforesaid statistics, we collected discharge time series during 30 years up to now; and consequently, we selected 10 acceptable flood hydrographs with suitable historical scattering. Later on, we performed and optimized MIKE11 flood routing model with definition of aforesaid statistics as input boundary conditions. Needless to say that although we used Manning coefficient (n) as the meaning of optimization parameter in MIKE11 hydrodynamic model; we estimated it through the main ZOSHK river with territorial reconnaissance.

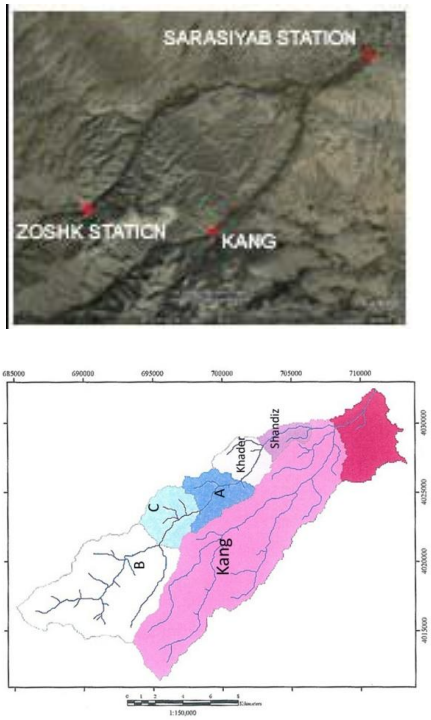

Fig. 3: Satellite Image of ZOSHK and KANG branches and chosen sub basins for them

As a termination of this stage, we analysed if output discharge was affected by any input data in previous time steps. To discover the answer, we tested and optimized MIKE11 model in four different stages. During the first stage we used each input hydrograph for modeling completely. Related output hydrograph is available in the column of RUN1 in table1 below. Then we processed the previous stage again but we eliminated first time step input record. Results are followed in aforesaid table (RUN2 column). We repeated this procedure for RUN3 and RUN4. Considering the table, we can say that third data in RUN1 is equal to second data in RUN2 with the accuracy of 0.1 as the first accordance of results in RUN1 and RUN2. It means that there is no difference between output results with the accuracy of 0.1 if we utilize at least two previous hourly discharge data as the input statistics for MIKE11 flood routing model. Comparison between columns RUN2 and RUN3; also, RUN3 and RUN4 confirm the same result. Furthermore, according to table1, we can say that for the accuracy of 0.01 at least six previous hourly input data was effective.

TABLE1. MIKE11 MODEL SENSITIVITY TO PREVIOUS TIME STEP INPUT STATISTICS

Output Sarasiyab-Shandiz (Run MIKE11)				Input		Time	Date
RUN4	RUN3	RUN2	RUN1	Kang	Zoshk		
				0.001	1.41	22:00:00	05/06/2007
			1.34731	0.001	1.41	23:00:00	05/06/2007
		1.34731	1.17807	0.001	1.41	00:00:00	05/06/2007
	1.34731	1.17807	1.12953	0.001	1.41	01:00:00	05/07/2007
1.35763	1.18841	1.13971	1.18361	0.012	1.61	02:00:00	05/07/2007
1.78816	1.74105	1.78342	1.7277	0.651	2.25	03:00:00	05/07/2007
3.7224	3.66605	3.71278	3.79705	2.591	4.4	04:00:00	05/07/2007
6.36695	6.41584	6.59725	6.60519	5.324	5.9	05:00:00	05/07/2007
9.17143	9.37289	9.37111	9.37112	8.091	8.0	06:00:00	05/07/2007
10.7596	10.7628	10.7628	10.7628	9.109	5.9	07:00:00	05/07/2007
12.0582	12.0582	12.0582		8.337	6.55	08:00:00	05/07/2007
13.9841	13.9841			8.045	3.95	09:00:00	05/07/2007
15.4389				8.2	4.6	10:00:00	05/07/2007

B. *Artificial Neural Networks*

Based on MILE11 model sensitivity analysis results, we supposed that output discharge in each time step could be affected by at most six previous time steps data. Consequently, according to Maskingam method which is an accepted flood routing method, we designed the structure of observed input and desired output data for artificial neural networks as below:

1) Input discharge in upstream station of main branch (ZOSHK hydrometric station) in 7 time steps (t_{-6}, t_{-5}, t_{-4}, t_{-3}, t_{-2}, t_{-1} and t_0).
2) Input discharge in secondary branch which enters the main branch (KANG branch) in 7 time steps (t_{-6}, t_{-5}, t_{-4}, t_{-3}, t_{-2}, t_{-1} and t_0).
3) Output discharge which calculated with MIKE11 in 7 time steps (t_{-6}, t_{-5}, t_{-4}, t_{-3}, t_{-2}, t_{-1} and t_0).
4) Output observed discharge in downstream station (SARASIYAB-SHANDIZ hydrometric station) in 6 previous time steps (t_{-6}, t_{-5}, t_{-4}, t_{-3}, t_{-2} and t_{-1}).
5) our desire output data for training artificial neural networks was observed discharge in downstream hydrometric station in each present time step (t_0).

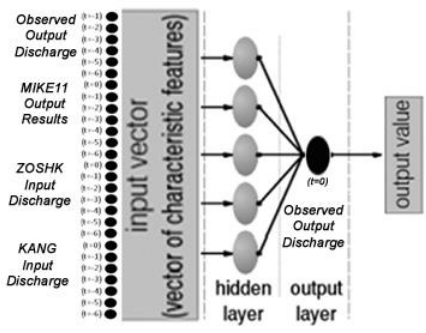

Fig. 4: First stage of input and Output definition in ANNs models.

Later on, we made specialized %70 of our ten chosen combinations of input and related observed output hydrographs which were recorded hourly in 30 years up to now (seven hydrographs) for training and validation, and %30 of them (three hydrographs) for different structures of artificial neutral networks testing which are presented in following table:

TABLE2. DIFFERENT UTILIZED STRUCTURES OF ANNS (FIRST STAGE).

Number of Structure	Structure	Hidden Layer			Output Layer	
		Number	Transformation Function	Training Algorithm	Transformation Function	Training Algorithm
1	MLP	1	Tanh	Mom	Linear	Mom
2	MLP	1	Tanh	CG	Linear	CG
3	MLP	1	Sig	Mom	Linear	Mom
4	MLP	1	Sig	CG	Linear	CG
5	GFF	1	Tanh	Mom	Linear	Mom
6	GFF	1	Tanh	CG	Linear	CG
7	GFF	1	Sig	Mom	Linear	Mom
8	GFF	1	Sig	CG	Linear	CG

Sensitivity analysis of the best choice to input discharge data between aforesaid structures is presented below:

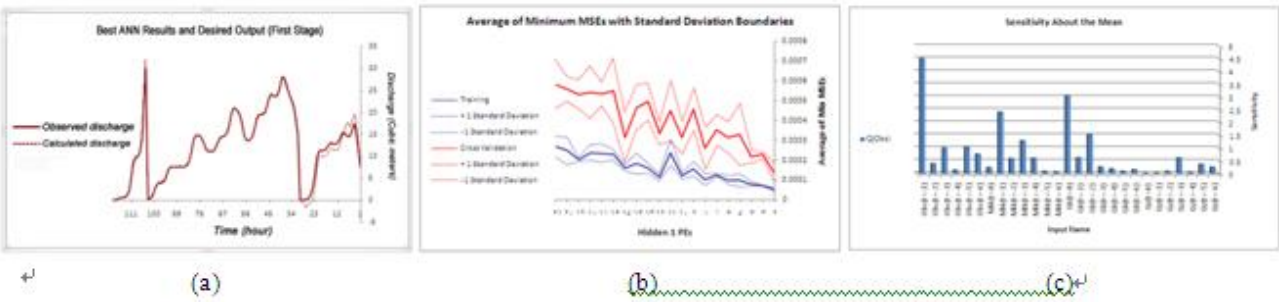

Fig. 5: First stage (Comparison of ANN results and observed ones, MSE and sensitivity analysis to the input data).

Although accuracy of results in compare with observed output statistics were really acceptable, some problems could be obviously seen which are discussed below:

1) There were some negative output statistics which were not acceptable according to physical conditions of flood discharge.
2) Differences between various tested networks results were obvious.
3) As it described before, we used output observed discharge in downstream station as the ANNs inputs; consequently, we could not run neural networks without observed output statistics existence.

TABLE3. DIFFERENT UTILIZED STRUCTURES OF ANNS (FINAL STAGE).

Number of Structure	Structure	Hidden Layer			Output Layer	
		Number	Transformation Function	Training Algorithm	Transformation Function	Training Algorithm
1	MLP	1	Tanh	Mom	Sig	Mom
2	MLP	1	Tanh	CG	Sig	CG
3	MLP	1	Sig	Mom	Sig	Mom
4	MLP	1	Sig	CG	Sig	CG
5	GFF	1	Tanh	Mom	Sig	Mom
6	GFF	1	Tanh	CG	Sig	CG
7	GFF	1	Sig	Mom	Sig	Mom
8	GFF	1	Sig	CG	Sig	CG

Furthermore, we found that difference between ANNs results in first stage had been occurred because of uncompleted training in some of them. So, in second stage we defined maximum 100 cycles of training. Moreover, to correct the results; and also, find out the most effective input hourly discharge, we reformed the structure of ANNs as table3.

III. RESULTS

Best results of final modeling stage which are related to fourth structure in table3 are available in graphs below. Looking at figure.6.a, we can say that acceptable artificial neural network results of testing hydrographs in compare with observed output statistics are obvious. In addition, considering figure.6.b, gradual decrease in MSE during training networks can be clearly seen.

Fig. 6: Final stage (Comparison of ANN results and observed ones, MSE and sensitivity analysis to the input data).

To wrap it up, we can say that comparing figure.6.c with figure.5.c makes it clear that both artificial neural networks sensitivity analysis to input discharge data and our utilized innovative procedure of MIKE11 model sensitivity analysis to input data results confirm at least two previous hourly input discharge time steps are effective in each time step output discharge prediction and calculation with accuracy of 0.1 In our case study flood routing modeling. Consequently, expanding results, we have to pay attention that choosing input discharge time extent at least two hours before modeling one causes error reduction and accuracy increase in flood routing modeling outputs.

IV. INDEX

CG: Conjugate Gradient, GFF: Generalized Feed Forward Networks, MLP: Multilayer Perceptron, MSE: Mean Square Error, Mom: Momentum, N: Number, n: Manning coefficient, Sig: Sigmoid Function, Tanh: Tangent Hyperbolic Function.

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