

Using FAST and Scatter Plot Methods For Sensitivity Analysis of Hydrologic Runoff Simulation

¹Rostam Taheri, ²Mehdi Fuladipanah, ³Amin Bordbar

^{1,3}Department of Irrigation, Khouzestan Science and Research Branch, Islamic Azad University (IAU), Ahvaz, Iran. ²Department of Civil Engineering, Ramhormoz Branch, Islamic Azad University, Ramhormoz, Iran.

ARTICLE INFO	ABSTRACT
Article history:	Background: River flow estimation has important role in water resources management.
Received 15 November 2013	SRM is a hydrologic model which has been used widely to estimate river flow in
Received in revised form 20	mountain catchment which snow and snowmelt have significant role in water supply of
January 2014	rivers. Objective: The model has ten input variables. Each variable has different
Accepted 25 January 2014	relation with model output. Determination of significant variables will increase model
Available online 5 March 2014	output reliability. In this paper, two approaches were applied to determine the
	sensitivity level of SRM inputs on its output: Fourier Amplitude Sensitivity Test which
Keywords:	is based on variance analysis, and Scatter Plot method. Results: High three Sensitivity
Sensitivity Analysis Variance	indices of FAST method were calculated for discharge of before day, Q as 0.26,
Analysis Scatter Plot Hydrologic	catchment area, A as 0.18, and percent of snow cover of catchment, S as 0.15.
Model	Minimum sensitivity index was calculated for temperature gradient. Conclusion: The
	most and the least variation of model output were plotted for the discharge of the day
	before and the temperature gradient based on scatter plot, respectively. On the other
	words, the results of two methods are unique.

© 2014 AENSI Publisher All rights reserved.

To Cite This Article: Rostam Taheri, Mehdi Fuladipanah, Amin Bordbar., Using FAST and Scatter Plot Methods For Sensitivity Analysis of Hydrologic Runoff Simulation. J. Appl. Sci. & Agric., 9(1): 33-37, 2014

INTRODUCTION

Sensitivity analysis is a technique to study relation between input and output factors of a model. Sensitivity analysis is one of very important processing of model developing. The general form of sensitivity analysis is presented in figure 1. Application of sensitivity analysis can be categorized as following:

• Which input parameters contribute the most to output variability and, possibly, require additional research to strengthen the knowledge base, thereby reducing output uncertainty.

- Which parameters are insignificant and can be eliminated from the final model;
- If and which (group of) parameters interact with each other;
- If all observed effects can be physically explained, when error may be present in a model;

• The optimal regions within the parameters space for use in a subsequent calibration study (Chan *et al.*, 1997).

It has been concerned researchers for many years (Johnson, 1996; Melching, 1995; Tang and Yen, 1972). It can be used to quantify and qualify uncertainties of model prediction (Hall, 2003; Hall and Solomatine, 2008). There are different methods to do sensitivity analysis, which can be categorized in three main classes as following: Derivative Based Sensitivity indices, Linear Regression, and Fourier Amplitude Sensitivity Test (Hall *et al.*, 2009). Two initial methods have some limitations which limits their application in hydrology and hydraulic (Chen and Chen, 2003; Cornell, 1972; Horritt, 2006; Indelman *et al.*, 1996; Kabala, 2001; Nash and Karney, 1999; Oliver and Smettem, 2005; Podsechin *et al.*, 2006; Manach and Melching, 2008; Pappenberger *et al.*, 2008).Unlike derivative and linear regression sensitivity analysis, there has to date been rather limited published application of these more general variance based sensitivity indices in the hydraulic engineering literature. The only three reported applications have been in the field of flood inundation modeling (Fuladipanah and Majedi, 2012). Fourier amplitude sensitivity Test (FAST) application has been proposed by researches (Cukier, 1973; Dawson *et al.*, 2008; Hall *et al.*, 2005; Pappenberger *et al.*, 2008). Because of hot and dry climate condition in Iran, water resources management plays very important role. More than 70% of surface water resources have been located in mountains catchment. In these basins, snow and snowmelt have very

Corresponding Author: Rostam Taheri, Department of Irrigation, Khouzestan Science and Research Branch, Islamic Azad University (IAU), Ahvaz, Iran. Email:R_taheri20@yahoo.com

Journal of Applied Science and Agriculture, 9(1) January 2014, Pages: 33-37

important role in the supply of river flow. Therefore, correct estimation of snowmelt will cause reasonable management of river flow.

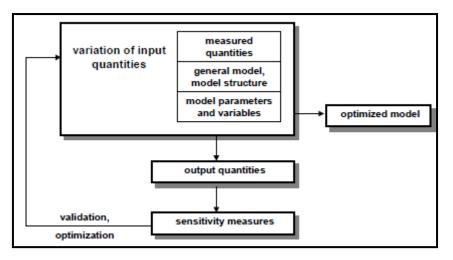


Fig. 1: general procedure of sensitivity analysis

Snowmelt Runoff Modeling is software to simulate and estimate daily river flow which originated from rain and snowmelt. The model has been used since 1972 in catchments of area of 10 to 1200 km2, which simulated and measured data have good agreement. The capability of SRM in flow simulation has been proven by researchers (Martinec *et al.*, 2008). The model has nine input factors which estimate model output. Therefore, it will be worthwhile to determine the sensitivity level of factors. In this paper, FAST method has been used to calculate sensitivity indices of SRM.

Methodology

2.1FAST Method

One measure of sensitivity of Y to an individual input variable Xi that is often used is V[E(Y|Xi)] i.e., the expected amount of variance that would be removed from the total output variance, if we were able to learn the true value of Xi. This is called main effect. After dividing by the total unconditional variance, first order sensitivity index for variable Xi is calculated:

$$S_i = \frac{V[E(Y|X_i)]}{V(Y)}$$
(1)

This measure indicates the relative importance of an individual input variable Xi. The total effect for the input variable Xi is linked to $E[V(Y|X\sim i)]$, which is the expected amount of output variance that would remain unexplained (residual variance) if Xi and only Xi were left free to vary over its uncertainty range, all the other variables having been learnt. After dividing by the total unconditional variance, total sensitivity index for variable Xi, is obtained as following:

$$ST_i = \frac{E[V(Y|X_{\sim i})]}{V(V)}$$

V(Y)

(2)

The total sensitivity indices are used in model developing to identify insignificant factors, i.e., the factors that are not important neither singularly nor in combination with others. All the input variables having a low total index can be frozen to any value within their range of uncertainty. Total indices should be employed to reduce the number of uncertain model inputs, i.e. for model simplification. The general procedure to get sensitivity measures for sample-based sensitivity analysis methods is given in the following (Fuladipanah and Majedi, 2012):

- 1. Definition of probability distributions functions for the input quantities
- 2. Generation of samples from the defined probability distributions
- 3. Evaluation of the model using the generated sample
- 4. Analysis of the output variance
- 5. Sensitivity analysis of the output variance in relation to the variation of the input quantities

2.2 Scatter Plot method:

Scatter plot is another method to determine sensitivity of a input factor. This method is a visualized procedure which is plotting a factor versus output of model. Scatter plots are the simplest form of analysis and

Mehdi Fuladipanah et al, 2014

Journal of Applied Science and Agriculture, 9(1) January 2014, Pages: 33-37

can reveal nonlinear relationships, parameter thresholds and, if plotted in two dimensions, variable interactions, which can aid in the understanding of model behavior (Saltelli *et al.*, 2005).

2.3 Snowmelt Runoff Modeling:

The SRM produces daily runoff according to the following equation:

$$Q_{n+1} = [C_{sn}a_n(T_n + \Delta T_n)S_n + C_{Rn}P_n] \frac{10000A}{86400} (1 - k_{n+1}) + Q_n k_{n+1}$$
(3)

Where Q is mean daily discharge, Cs and CR are snow and rain runoff coefficients, respectively, a is degree-day factor, T and Δ T are number of degree-days and adjustment by temperature lapse rate, respectively, S is percent of the snow covered area, P is precipitation, A is area of the basin or zone, and k is recession coefficient (Martinec *et al.*, 2008).

RESULTS AND DISCUSSION

Five mentioned steps were used to do FAST method of SRM. Steps 1 and 2 are presented in table 1. Using input variable in table 1, model was run. Each factor was tested of number 10000. The results of step 5 are presented in table 2. As it seen, the highest values of sensitivity indices are belong to: Q, A, S, P, k, T, Cs, CR, a and ΔT , respectively. Sensitivity indices for three influence input factors are calculated as 0.26, 0.18, and 0.15. The comparison of these data, illustrates that discharge of the day before, catchment area and percent of snow cover are very significant factors which should be evaluated accurately. The least influence parameter is temperature gradient which its sensitivity index is calculated as 0.009. The sum of sensitivity analysis is 0.8932 which is greater than 0.6. This criterion shows the acceptable results of variance based sensitivity analysis. But, the sum of sensitivity indices is less than 1. On the other word, SRM is not an additive model. Fig. 2 shows diagrammatic schematic view of table 2. Therefore, it is very important the flow discharge, catchment area and snow cover of catchment measured accurately than the other input variables. Figs. 3 and 4 are scatter plot of the most and the least influence factors versus model output. As it clear, dispersion of model output in Fig. 3 is more than Fig. 4. On the other words, variation of ΔT has no significance effect on model output.

Table 1:	input	factors	distribution	of SRM	model
----------	-------	---------	--------------	--------	-------

Variables	Distribution type	Input factors	
Cs	Log-Normal	(0.1,0.9)	
a	Log-Normal	(0.5,3)	
Т	Normal	(-20,20)	
ΔT	Log-Normal	(0.001,0.009)	
S	Normal	(0.1,1)	
C _R	Normal	(0.1,0.9)	
Р	Log-Normal	(0.5,15)	
А	Normal	(10,10000)	
k	Log-Normal	(0.5,4)	
Q	Log-Normal	(5,4000)	

Table 2: FAST method results of SRM

Variables	Si	S _{Ti}
Cs	0.015	0.066
a	0.01	0.071
Т	0.053	0.096
ΔΤ	0.009	0.059
S	0.15	0.3
C _R	0.012	0.13
Р	0.1042	0.27
А	0.18	0.25
k	0.10	0.33
Q	0.26	0.49
Total	0.8932	-

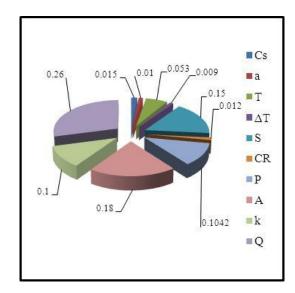


Fig. 2: schematic view of FAST method

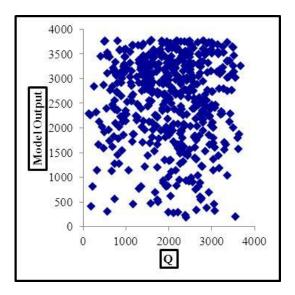


Fig. 3: Scatter plot of discharge of the day before vs model output

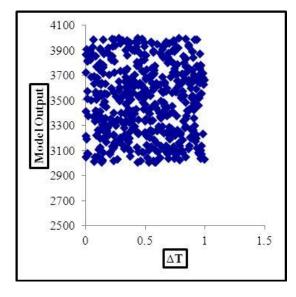


Fig. 4: Scatter plot of temperature gradient vs model output

Journal of Applied Science and Agriculture, 9(1) January 2014, Pages: 33-37

REFERENCES

Chan, K., A. Saltelli and S. Tarantola, 1997. Sensitivity analysis of model output: variance based methods make the difference. Proceeding of the 1997 winter simulation conference, Ispra, Italy.

Chen, X., X. Chen, 2003. Sensitivity analysis and determination of streambed leakance and aquifer hydraulic properties. Journal of Hydrology, 284: 270-284.

Cornell, C.A., 1972. First-order analysis of model and parameter uncertainty.Proc., Int. Symp.on Uncertainties in Hydrology and Water Resources Systems, University of Arizona, Tucson, Ariz., pp: 1245-1272.

Cukier, R., C. Fortuin, K. Shuler, A. Petschek, and J. Schaibly, 1973. Study of the sensitivity of coupled reaction systems to uncertainties in rate coefficients. I Theory. J. Chem. Phys., 59(8): 3873-3878.

Dawson, R.J., L. Speight, J.W. Hall, S. Djordjevic, D. Savic, and J. Leandro, 2008. Attribution of flood risk in urban areas. J. Hydroinform., 10(4): 275-288.

Fuladipanah, M., M. Majediasl, 2012. Sensitivity Analysis of Movable Bed Roughness Formula in Sandy Rivers, journal of civil engineering and urbanism, 2(5): 187-190.

Hall, J.W., 2003. Handling uncertainty in the hydro-informatic process. J. Hydroinform., 5(4): 215-232.

Hall, J.W., D. Solomatine, 2008. A framework for uncertainty analysis in flood risk management decisions. J. River Basin Manage., 6(2): 85-98.

Hall, J.W., S.A. Boyce, Y. Wang, R.J. Dawson, S. Tarantola, and A. Saltelli, 2009. Sensitivity analysis for hydraulic models. ASCE, 135(11): 959-969.

Hall, J.W., S. Tarantola, P.D. Bates, and M.S. Horritt, 2005.Distributed sensitivity analysis of flood inundation model calibration. J. Hydraul. Eng., 131(2): 117-126.

Horritt, M.S., 2006. A linearized approach to flow resistance uncertainty in a 2-D finite volume model of flood flow. Journal of Hydrology, 316: 13-27.

Indelman, P., G. Dagan, A. Cheng, and D. Ouazar, 1996. Sensitivity analysis of flow in multilayered leaky aquifer systems. J. Hydraul. Eng., 122(1): 41-45.

Johnson, P.A., 1996. Uncertainty of hydraulic parameters. J. Hydraul. Eng., 122(2): 112-114.

Kabala, Z.J., 2001. Sensitivity analysis of a pumping test on a well with wellbore storage and skin. Adv. Water Resour., 24: 483-504.

Manache, G., and C.S. Melching, 2008. Dentification of reliable regression- and correlation-based sensitivity measures for importance ranking of water-quality model parameters. Environmental Modeling Software, 23(5): 549-562.

Martinec, J., A. Rango, and R. Roberts, 2008. Snowmelt Runoff Model (SRM) User's Manual. New Mexico State University, Las Cruces, NM Melching, C.S., 1995. Reliability estimation. Computer models of watershed hydrology, V. P. Singh, ed., Water Resources, Littleton, Colo., pp: 69-118.

Nash, G.A., B.W. Karney, 1999. Efficient inverse transient analysis in series pipe systems. J. Hydraul. Eng., 125(7): 761-764.

Oliver, Y.M., K.R.J. Smettem, 2005. Predicting water balance in a sandy soil: Model sensitivity to the variability of measured saturated and near saturated hydraulic properties. Austral. J. Soil Res., 43: 87-96.

Pappenberger, F., M. Ratto, K.J. Beven, and P. Matgen, 2008. Multi-objective global sensitivity analysis of flood inundation models. Adv. Water Resour., 31(1): 1-14.

Podsechin, V., I. Tejakusuma, G. Schernewski and M. Pejrup, 2006. On parameters estimation in dynamic model of suspended sediments. J. Hydrol., 318: 17-23.

Tang, W.H., B.C. Yen, 1972. Hydrologic and hydraulic design under uncertainties. Proc. Int. Symp. on Uncertainties in Hydrology and Water Resources Systems, University of Arizona, Tucson, riz., pp: 868-882.