IDENTIFICATION OF ROUGHNESS IN OPEN CHANNELS

Hien T. Nguyen[1] and John D. Fenton[2]

ABSTRACT

At present, the studies on the inverse problem of identifying roughness values have been mainly for in-bank flow problem that needs to extend the method to out-bank flow where flood plain roughness obviously has to be considered. In this study, the inverse problem of estimating the open channel flow roughness values has been studied for both single channel problem and compound channel problem by using synthetic data. The effects of selection of objective functions on the quality of the identified parameter are analysed for a single channel reach. The results indicate that the least square errors objective function has the best performance. For compound channels, the performance of the model is evaluated for different scenarios of data availability, sizes of peak discharge and noise in flow measurement data on the quality of the identified parameters. Solution results for illustrative problems indicate the potential applicability of the model to the natural channels.

1. INTRODUCTION

Flood routing in open channel is of vital importance to river engineers and managers. The basic equations can be derived from the principles of conservation of mass and momentum. The resulting equations are hyperbolic, non-linear differential equations known as the Saint-Venant equations. The channel roughness coefficient as embedded in the momentum equation cannot be measured directly and therefore needs to be estimated. An accurate estimation of Manning's roughness coefficient is of primary importance in any study involving open-channel flow.

In the numerical modelling of unsteady flows in open channels, the problem of identifying the values of roughness parameters embedded in the Saint-Venant equations using automatic optimization methods is referred to as the inverse problem. There is a wide range of objective functions and optimization methods. Becker and Yeh (1972,1973) used the influence coefficient approach by minimizing the sum of squares of differences between observed data and numerically simulated values to estimate the parameters. Wiggert et al. (1976) employed a conjugate gradient method and formulated the objective function by using the sum of the absolute difference between observed and simulated stages and discharges at intermediate sections. Fread and Smith (1978) used a modified Newton-Raphson search technique for estimating the roughness parameter as a function of stage and discharge. They minimized the absolute value of the sum of the difference between

[1] PhD Student, Department of Civil and Environmental Engineering, The University of Melbourne, Victoria, Australia 3010 (thuhien@civenv.unimelb.edu.au)
[2] Professor Fellow, Department of Civil and Environmental Engineering, The University of Melbourne, Victoria, Australia 3010 (fenton@unimelb.edu.au)

observed and computed stages and discharges. However, their method required breaking down the river into a number of single channel reaches before calibrating each reach separately. Wormleaton and Karmegam (1984) formulated the objective function in terms of relative errors using both depth and discharge values and identified the parameters with the influence coefficient algorithm and also a nonlinear least-square technique. Khatibi et al. (1997) used a nonlinear least square technique with three types of objective function by a modified Gauss-Newton method. They investigated the statistical behaviour of the errors induced in the identified parameter in response to Gaussian noise as normally contained in the observed data. Atanov et al. (1999) introduced a variational approach of Lagrangian multipliers using a least square errors criterion to estimate roughness coefficients. However, the algorithm can be applied only to simple prismatic channels. The Sequential Quadratic Programming Algorithm was used by Ramesh et al. (2000) to minimize the objective function based on the least square error criterion. The computation was carried for different scenarios of data availability and noise in flow measurement data.

In flood routing in natural rivers, most channels have compound sections and the roughness values in main channel and flood plains are usually different. However, these studies have just considered roughness parameters in the in-bank channel. Therefore, this problem needs to extend the method to out-bank flow where flood plain roughness will obviously have to be considered. In this study the inverse problem of estimating the open channel flow roughness values has been studied for both single channel problem and compound channel problem by using synthetic data. The effects of selection of objective functions on the quality of the identified parameter are analysed for a single channel reach with different data noise levels, in which three common objective functions (minimizing sum of square errors, sum of absolute errors and maximum error) are considered. For compound channels, the true values of roughness in the main channel and flood plains are presented as two different values, one for main channel and the other for flood plain. The performance of the model is evaluated for different scenarios of data availability, sizes of peak discharge (time and flood level in flood plains) and noise in flow measurement data on the quality of the identified parameters.

2. THEORY

2.1 Numerical Modelling for Unsteady Flow in Open Channel

The unsteady one-dimensional open-channel equations can be derived from the principles of conservation of mass and momentum resulting in equations known as the Saint-Venant equations:

$$\frac{\partial A}{\partial t}+\frac{\partial Q}{\partial x}=q \tag{1}$$

$$\frac{\partial Q}{\partial t}+2\beta\frac{Q}{A}\frac{\partial Q}{\partial x}+\left(gA-\beta\frac{Q^2B}{A^2}\right)\frac{\partial Z}{\partial x}-\beta\frac{Q^2B}{A^2}S_0+gAS_f-u_q q=0 \tag{2}$$

where: A is wetted cross-sectional area; Q is discharge; Z is water stage or surface water elevation; q is lateral inflow per unit length of channel; B is channel width at the surface water; β is momentum correction factor; g is gravity acceleration; S_0 is channel bed slope; S_f is friction slope; u_q is the x direction velocity component of the lateral inflow; x and t are space and time variables respectively.

The friction slope S_f is given by Manning's equation:

$$S_f = \frac{Q|Q|}{K^2} = \frac{n^2 Q|Q|}{A^2 R^{4/3}} \tag{3}$$

where: K is the conveyance, R is the hydraulic radius, n is Manning roughness coefficient.

For compound channels, the critical assumption is that friction slope is constant in main channel and floodplains. The conveyance is computed using divided section method in which for any depth the conveyance of the compound section is the sum of the main channel and floodplain conveyances. Then:

$$S_f = \frac{Q_1|Q_1|}{K_1^2} = \frac{Q_2|Q_2|}{K_2^2} = \frac{Q_3|Q_3|}{K_3^2} = \frac{Q|Q|}{(\sum K_i)^2} \tag{4}$$

where: K_1, K_3 and Q_1, Q_3 are the conveyances and discharges of floodplains, K_2 and Q_2 are the conveyance and discharge of main channel, Q is the total discharge of the section.

In this study, the Saint-Vernant equations are solved by the implicit finite deference Preissmann box scheme. The algebraic equation system is linearised and solved by using double sweep algorithm (Liggett and Cunge (1975), Cunge (1980)).

2.2 Identification of Roughness in Open Channels

The capability for the identification of the roughness coefficient of the model river is based on minimizing a chosen objective function. There are many types of objective functions some common objective functions will be mentioned in the next part. The roughness identification procedure is illustrated similar to Solomatine (1998) in Figure 1. The procedure starts with initial estimated parameters and performs a completed simulation run. The objective functions are evaluated by comparing the observed data against the simulated ones by the model. If the value of the function is above the prescribed tolerance value, the process is continued iteratively through computing a correction to the parameters by using an optimisation algorithm.

2.3 Choosing Objective Functions

Khabiti et al. (1997) indicated that the selection of objective function was found to be prone to undue biases affecting the identified parameters, which could be avoided through a careful consideration of the problem. They considered the sum of square of errors using absolute errors, relative errors with respect to observed values and relative errors with respect to simulated values. They concluded that the formulation of the objective function using relative errors seems to induce an undue bias that increase with increasing noise level. Therefore, in this study three main types of objective function using absolute errors will be considered as follows:

Minimising sum of squares errors between observed and simulated stages/discharges:

$$\min \sum_{i=1}^{T} (Y_{o,i} - Y_{s,i})^2 \tag{5}$$

Minimising sum of the absolute errors:

$$\min \sum_{i=1}^{T} \left| Y_{o,i} - Y_{s,i} \right| \tag{6}$$

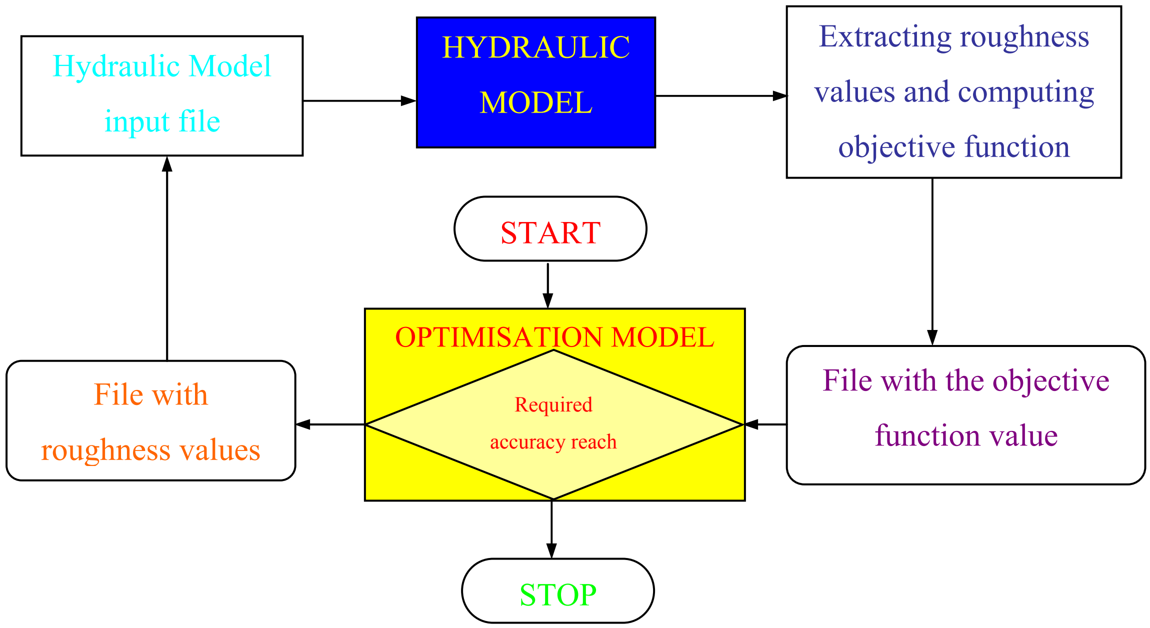

Figure 1 The roughness identification procedure

Minimising the maximum error:

$$\min\left[\max_{i=1}^{T}\left|Y_{o,i}-Y_{s,i}\right|\right] \tag{7}$$

where: i is temporal subscript, Y_o is observed discharges or stages, Y_s is simulated discharges or stages, T is total observation time.

3. PERFORMANCE EVALUATION

Performance of the model for identification of roughness coefficients is valuated using synthetic data for hypothetical open channel reaches. These example problems include 2 cases. The first case is flow in simple channel with single value of n for the whole reach. The second one is a compound channel reach with difference roughness values corresponding to main channel and flood plains.

Because in the field the true value of roughness is not known, the advantage of using synthetic data is that it is possible to make comparisons between the estimated n with the true value n. This can provide the abilities to evaluate the performance of the model and investigate some factors that affect the quality of the identification problem.

The observed gauge station is located at intermediate section of the channel. The observation data for these cases are simulated by solving governing equation (1) and (2) with the true values n. Identical initial and boundary conditions are applied while obtaining the simulated observation data and while solving the optimisation models.

3.1 Identification of Roughness for Single Roughness Channels

For single channels problem, the ability to identify the channel roughness of the proposed model is investigated in term of types of objective function (three common types are mentioned above) with different noise levels of observed data. In this case, ACCOL algorithm of GLOBE software developed by Solomatine (1995) is applied to the problem. This algorithm is the combination of Adaptive Clustering Covering Optimisation with subsequent of direct Powell-Brent method of the Local search. The details of this algorithm are described in Solomatine (1995, 1998). This algorithm is chosen for this case because it can give very accurate results for all the three objective functions. In this case, the hydraulic model works as external program where the value of the objective function is computed. The roughness identification procedure is illustrated in Figure 1.

Synthetic data: A model channel has a length of 40 km with slope of 0.0004, the cross section of a 50m wide and sideslope (batter) of 1.5. The Manning *n* value of 0.025 is selected for the whole channel reach. The downstream boundary condition is the stage hydrograph at 40 km point in a 80 km long channel. The down stream boundary condition for the 80 km channel, which has the same channel properties and upstream boundary condition as the 40 km channel, is a steady uniform rating function. The upstream boundary condition is the synthetic hydrograph generated by:

$$Q(t) = Q_b + (Q_p - Q_b)\left[\frac{t}{t_p}\exp\left(1 - \frac{t}{t_p}\right)\right]^{\beta} \quad (8)$$

where Q_b is initial discharge, Q_p is peak discharge and t_p is time to peak, β is a constant. In this case $Q_b = 200$ m^3/s, $Q_p = 500$ m^3/s, $t_p = 4$ hours and $\beta = 5$.

In practice, flow measurement data usually contain observation errors/noise. Also, in mathematical modelling the other error sources are "model errors" and "numerical errors". "Model errors" are associated with imperfections of the governing equation and some restricted assumptions to simplify the physical processes. "Numerical errors" include rounded errors, truncation errors related to the finite different methods. These random errors are generally thought to be normally distributed (Khabiti et al. (1997)). In this study, the noise is introduced into the simulated observed discharges or depths (noise free) Y_o as follows:

$$Y_o^n = Y_o + \varepsilon Y_o \quad (9)$$

where Y_o^n is the simulated observed data with noise level σ, $\varepsilon = N(\mu,\sigma)$ is a random error term sampled from a normal distribution of zero mean and standard deviation of σ.

The computed results are summarised in Table 1. From the table it can be seen that the computed results are very good. For the case of the noise-free observation data, all three types of objective function give similar and very accurate values for *n*. To consider the effect of the noise contained in observed data, four difference noise levels of σ=0.05, 0.10, 0.15 0.02 are considered. 20 samples of each noise level are generated from different of seeding random numbers. For any given noise level the individual values of identified parameter deviate from the true value and As expected the higher the noise level is the wider the range of identified parameters. However, these identified values scatters around the true value and the average values of identified *n* for all three objective functions are very close to the true one. The results also indicate that the least square objective function performs better compared with the two other objective functions because the dispersion level is lowest (range of identified *n* is the narrowest).

Table 1 Effect of different objective functions with different noise levels of observed data (the true value of *n* is 0.025)

Objective Function	Noise level	Range of identified *n* (20 samples)	Average of identified *n* (20 samples)
Minimising sum of square errors (Equation 5)	0.00	0.02500	0.02500
	0.05	0.02430 – 0.02555	0.02503
	0.10	0.02368 – 0.02619	0.02489
	0.15	0.02334 – 0.02694	0.02507
	0.20	0.02283 – 0.02756	0.02507
Minimising sum absolute errors (Equation 6)	0.00	0.02500	0.02500
	0.05	0.02420 – 0.02573	0.02506
	0.10	0.02356 – 0.02684	0.02470
	0.15	0.02307 – 0.02743	0.02517
	0.20	0.02278 – 0.02781	0.02485
Minimising the maximum error (Equation 7)	0.00	0.02500	0.02500
	0.05	0.02347 – 0.02614	0.02503
	0.10	0.02239 – 0.02746	0.02495
	0.15	0.02093 – 0.02878	0.02455
	0.20	0.01952 – 0.03040	0.02487

3.2 Identification of Roughness for Compound Channels

In this case, the true values of roughness in the main channel and flood plains are presented as two different values, one for main channel and the other for flood plain. As the above results, the objective function of least square errors between observed and simulated discharge/stage is the best one so it is chosen for this inverse problem and solved by Powell optimisation algorithm (Powell (1965), Press et al. (1992)). The performance of the model is evaluated for different scenarios of data availability, sizes of peak discharge (time and flood level in flood plains) and when measurement data contain noise. on the quality of the identified parameters.

Synthetic data: A model channel has a length of 40 km with slope of 0.0004. The geometry of the compound cross section is illustrated in Figure 2. The sideslopes of the cross section for both main channel and flood plain are 1.5. The true roughness values of main channel (n_c) and flood plains (n_f) are 0.028 and 0.042 respectively, which are selected for the whole channel reach. The stage hydrograph is chosen as the downstream boundary condition and generated similar to the single channel reached. The discharge hydrograph is chosen as the upstream boundary condition followed Equation (8) where $Q_b = 200$ m^3/s, $t_p = 10$ hours and, $\beta = 5$ and different values of $Q_p = 700$, 900 and 1200m^3/s.

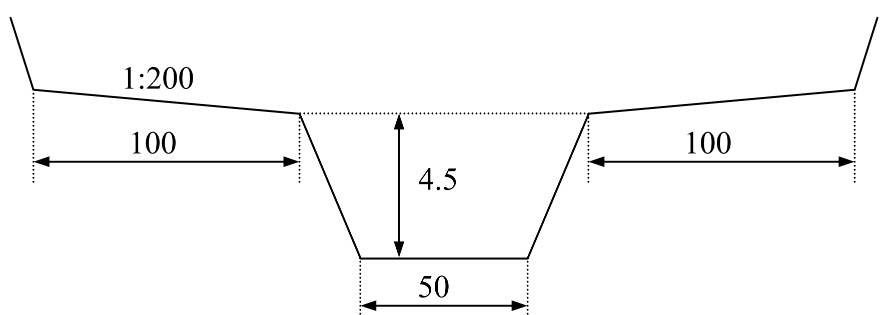

Figure 2 The cross section of the compound channel

Effect of data availability in term of observation intervals on the roughness identification:
In order to investigate the effect of observation intervals on the quality of identified parameters, several intervals with the same flood of $Q_p = 1200\,\text{m}^3$/s are considered including 0.5 hour, 1 hour, 2 hours and 4 hours. Table 2 shows the computed roughness value obtained from the model are very accurate when the data have no noise (the results for these cases are show up to 8 decimals to indicate the accuracy of the identified roughness). When data contain noise of $\sigma = 0.05$ although the main channel roughness can be identified rather accurate (the maximum error is less than 3%) the

Table 2 Effect of observation intervals on the roughness identification
(the true values of n_c and n_f is 0.028 and 0.042 respectively)

Interval (hours)	No noise		Noise of $\sigma = 0.05$				
	n_c	n_f	Sample	n_c	% error* of n_c	n_f	% error* of n_f
0.5	0.02800015	0.04299941	1	0.02796	-0.14	0.04129	-1.69
			2	0.02819	0.67	0.03917	-6.73
			3	0.02797	-0.11	0.04227	0.64
			4	0.02825	0.89	0.04123	-1.83
			5	0.02800	0.00	0.04290	2.14
1.0	0.02800034	0.04199972	1	0.02815	0.54	0.03982	-5.04
			2	0.02778	-0.79	0.04534	7.95
			3	0.02788	-0.43	0.03927	-6.50
			4	0.02810	0.36	0.03960	-5.71
			5	0.02772	-1.00	0.04370	4.05
2.0	0.02800090	0.04199972	1	0.02752	-1.71	0.03642	-13.29
			2	0.02815	0.54	0.04734	12.71
			3	0.02791	-0.32	0.04358	3.76
			4	0.02756	-1.57	0.04378	4.24
			5	0.02838	1.36	0.03671	-12.60
4.0	0.02799953	0.04199924	1	0.02874	2.64	0.03660	-12.86
			2	0.02800	0.00	0.05318	26.62
			3	0.02863	2.25	0.03237	-22.93
			4	0.02847	1.68	0.04134	-1.57
			5	0.02787	-0.46	0.03838	-8.62

- % error in identified n is defined as: $(n_{comp}-n_{true})/n_{true}$

flood plain roughness is bias from the true one. From the table it can be seen that the smaller the observation interval is the better the identified parameters. For example, when observation interval is 1 hours the relative maximum error for 5 samples is less than 8% but when the observation interval is 4 hours the relative maximum error is up to 27%. The reason of this bias is the number of observed data during the flood plains are flooded is too few and contained the errors so that could not reflect the real value of flood plain roughness.

Effect of difference peak discharges on the roughness identification:

Three peak discharges of 700, 900, and 1200 $\text{m}^{3/}$s are considered for the same channel as above with the same observation interval of 1 hour. The effect of peak discharge on the quality of roughness identification is shown in Table 3. The results indicate that when there are no noise contained in the observed data, the model can obtain very accurate the values of roughness for the compound channel even when the flooded level in flood plains is small for the case of the peak discharge of 700m^3/s (the flooded depth in the flood plains is 0.71m and flooded time is about 10 hours).

Table 3 Effect of peak discharges on the roughness identification
(the true values of n_c and n_f is 0.028 and 0.042 respectively)

Peak discharge (m3/s)	No noise		Noise of σ = 0.05				
	n_c	n_f	Sample	n_c	% error of n_c	n_f	% error of n_f
700	0.02799988	0.04200684	1	0.02843	1.54	0.03732	-11.14
			2	0.02770	-1.07	0.03086	-26.52
			3	0.02790	-0.36	0.04978	18.52
			4	0.02820	0.71	0.03233	-23.02
			5	0.02774	-0.93	0.05465	30.12
900	0.02799980	0.04199969	1	0.02767	-1.18	0.03800	-9.52
			2	0.02780	-0.71	0.04667	11.12
			3	0.02795	-0.18	0.04023	-4.21
			4	0.02765	-1.25	0.04152	-1.14
			5	0.02806	0.21	0.03566	-16.00
1200	0.02800034	0.04199923	1	0.02815	0.54	0.03982	-5.04
			2	0.02778	-0.79	0.04534	7.95
			3	0.02788	-0.43	0.03927	-6.50
			4	0.02810	0.36	0.03960	-5.71
			5	0.02772	-1.00	0.04370	4.05

However, as may be expected when the data contained noise although the computed roughness value of the main channel for different floods are quite close with the true one, the identified roughness value of flood plain is biased from the true one. The computed results in Table 3 also indicate that the larger the peak discharge is the more accurate the identified flood plain roughness. The reason of this bias is the same with the cases of the long observation intervals that the number of observation data points during flooding time is too few that is not enough to reflect the real value of flood plain roughness.

Therefore the selection of a historic flood are one of important factor that affects the quality of identified roughness values of a river reach especially for reaches with flood plains. It is suggested that in order to obtain more accurate results the number of observed data points during inundated time should be long enough that can be obtained by choosing a flood with long flooded time or high frequency of observation.

4. CONCLUSIONS

In this study, the inverse problem of estimating the open channel flow roughness values has been studied for both single channels and compound channels by using synthetic data. For a single channel reach, the effects of selection of objective functions and different data noise levels are analysed. The results indicate that the least square errors objective function has a best performance. For compound channels, the true values of roughness in the main channel and flood plains are presented as two different values, one for main channel and the other for flood plain. The performance of the model is evaluated for different scenarios of data availability, sizes of peak discharge (time and flood level in flood plains) and noise in flow measurement data on the quality of the identified parameters. It is shown that choosing a flood event is one of important factor on the quality of identifying the roughness values for both main channel and flood plain. In order to obtain accurate results the chosen flood data should be long enough especially during the flooding time. Solution results for illustrative problems indicate the potential applicability of the model to the natural channels.

REFERENCES

Atanov, G.A., Evseeva, E.G. and Meselhe, E. A. (1999). "Estimation Of Roughness Profile In Trapezoidal Open Channel", Journal of Hydraulic Engineering, Vol. 125, No. 3**,** 309-312.

Becker, L. and Yeh, W.W.G. (1973). "Identification of Multiple Reach Channel Parameters", Water Resources Research, Vol. 9, No. 2, 326-335.

Becker, L. and Yeh, W.W.G. (1972). "Identification of Parameters in Unsteady Open Channel Flows", Water Resources Research, Vol. 8, No. 4, 956-965.

Cunge, J.A., Holly, F.M., Verwey, A. (1980). Practical Aspects of Computational River Hydraulics, Pitman, London.

Fread, D. L. and Smith, G F (1978). "Calibration Technique for 1-D Unsteady Flow Models", ASCE Proc., Journal of Hydraulic Division, Vol. 104, No. 7, 1007-1044.

Khatibi, R.H., Willians, J.J.R and Wormleaton, P.R (1997). "Identification Problem of Open-Channel Friction Parameters", Journal of Hydraulic Engineering, Vol. 123, No. 12, 1078-1088

Liggett, J.A., Cunge, J.A. (1975). "Numerical Methods of Solution of The Unsteady Flow Equations", Chapter 4 of Unsteady Flow in Open Channels, Water Resources Publication, Fort Collins, Colorado.

Powell, M. J. D. (1965). "A Method For Minimizing A Sum Of Square Of Nonlinear Function Without Calculating Derivatives", The Computer Journal, No. 7, 303-307.

Press, W.H., Teukolsky, S.A., Vettering, W.T. and Flannery, B.P. (1992). Numerical Recipes in Fortran- The Art of Science Computing-Second Edition. Cambridge University Press, New York, N.Y.

Ramesh, R., Datta, B., Bhallamudi, S.M. and Narayana, A. "Optimal Estimation of Roughness in Open Channel Flows". Journal of Hydraulic Engineering, Vol. 126, No. 4: 299-303.

Solomatine, D.P. (1995). "The use of global random search methods for models calibration". Proc. XXVIth Congress of the International Association for Hydraulic Research, London, September 1995.

Solomatine, D.P. "Genetic and other global optimization algorithms – comparison and use in calibration problems", Proc. 3 th International Conference on Hydroinformatics, Copenhagem, Denmark, 1998. Balkema Publishers, 1021-1028.

Wiggert, J.M., Taylor M.R., and Contrator, D.N. (1976). "Optimization of an Implicit Scheme Flow Routing Model", International Symposium on Unsteady Flow in Open Channels. University of Newcastle-on-Tyne, BHRA fluid Engineering, Cranfield, Bedford, England.

Wormleaton, P.R. and Karmegam, M. (1984). "Parameter Optimization in Flood Routing". ASCE Proc., Journal of Hydraulic Division, Vol. 102, No. 12, 1799-1810.

Yeh, W.W.G, and Becker, L. (1973). "Linear Programming and Channel Flow Identification", ASCE Proc., Journal of Hydraulic Division, Vol. 99, No. 11, 2013-2021.