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Estimation of Open Channel Roughness by using Gradual Varied Flow Profiles

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Abstract: ***Open channel flow parameter estimation is an inverse problem, which involves the prediction of a function within a domain, given an error criterion with respect to a set of observed data. Various numerical methods have been developed to estimate open channel flow parameters. For this study, Genetic Algorithm optimization technique is selected. Because of its inherent characteristics, Genetic Algorithm optimization technique avoids the subjectivity, long computation time and ill-posedness often associated with conventional optimization techniques. An accurate estimation of roughness coefficients is of vital importance in any open channel flow study. In flood routing in natural rivers, most channels have compound sections and the roughness values in main channel and flood plains are usually different. In order to have more accurate results, the roughness of main channel and flood plains should be considered separately. It is possible to identify the values of roughness using optimization methods. However, studies on the inverse problem of estimating roughness values in compound channels are still limited. The present study involves estimation of open channel flow parameters having different bed materials invoking data of Gradual Varied Flow (GVF). Use of GVF data facilitates estimation of flow parameters. The necessary data base was generated by conducting laboratory experiments in Hydraulics Lab of civil Engineering at IIT Roorkee. In the present study, the efficacy of the Genetic Algorithm (GA) optimization technique is assessed in estimation of open channel flow parameters from the collected experimental data. Computer codes are developed to obtain optimal flow parameters Optimization Technique. Applicability, Adequacy & robustness of the developed code are tested using sets of theoretical data generated by experimental work. Estimation of Manning's Roughness coefficient from the collected experimental work data by using Manning's equation & GVF equation were made. The model is designed to arrive at such values of the decision variables that permit minimized mismatch between the observed & the computed GVF profiles. A simulation model was developed to compute GVF depths at preselected discrete sections for given downstream head and discharge rate. This model is linked to an optimizer to estimate optimal value of decision variables. The proposed model is employed to a set of laboratory data for three bed materials (i.e, d_{50}=20mm, d_{50}=6mm and lined concrete). Application of proposed model reveals that optimal value of fitting parameter ranges from 1.42 to 1.48 as the material gets finer. This value differs from the currently documented value i.e. 1.5. The optimal estimates of Manning's n of three different bed conditions of experimental channel appear to be higher than the corresponding reported / Strickler's' estimates.***

Keywords: Estimation of open channel roughness, GVF profiles, parameter estimation, optimization methods, Manning's roughness coefficient.

1. Introduction

1.1 General

Nowadays, models are decision-making tools but their reliability depends considerably on the choice of these parameters. In practice, their values are obtained through tedious trial-and-error procedures mainly involving visual comparisons. There is clearly scope for improvement by applying automatic optimization methods for the introduction of objectivity and efficiency into the procedure. In general, parameters in mathematical models applied in the field of hydraulic engineering can be categorized into physical parameters and empirical parameters. Physical parameters describe physical properties and features of materials, e.g., the density of fluid. They usually are constants and probably have a set of independent state equations connected with some physical variables. Empirical parameters are based on mathematical models without definite and complete physical concept. Due to complexities of physical processes, the exact values of empirical parameters, such as Manning's **n** in shallow water equations, are often uncertain. These kinds of empirical parameters are widely used in process modeling. As an empirical parameter, Manning's **n** actually includes the components of surface friction resistance, form resistance, wave resistance, and resistance due to flow unsteadiness. Many empirical formulations for estimating the **n** value in practical problems have been suggested in the past (Urquhart 1975).

Roughness and flow estimation from given flow profiles for rivers having multiple estuaries is an important problem. The estuaries may be interconnected and form closed-loop channel networks.

The resulting distributed parameter system may hinder the roughness and flow estimation because of the gradually varied flow effects. This paper documents the development of optimization models for parameter estimation in closed-loop channel networks. The parameter estimation procedure determines a set of unknown parameter values by minimizing the difference between the model-predicted water surface profile and observed values. The approach is known as inverse solution of the open-channel flow problem, and it stands as an independent area of research in many fields of engineering applications. For example, in the groundwater literature, Willis and Yeh (1987) reported a large number of inverse problem studies and in open-channel hydraulics, Yeh and Becker (1973) and Khatibi et al. (1997) reported the solution of inverse problems for transient flow in a single channel. The present study considers steady-state flow in closed-loop channel networks. Two approaches can be used for solving inverse problems. The first is an iterative solution in which a numerical model is used to compute the water surface profiles for a given set of input parameter values and the computed water surface profile is then compared with the known water surface profiles for minimum error. Such a procedure can be computationally demanding. The present study uses the second approach, which combines the numerical procedure of the first approach in an optimization model that minimizes the error between the computed and observed water surface elevations, subject to satisfaction of the governing equations for flow in closed-loop channel networks.

Genetic programming (GP – an extension of genetic algorithms to the domain of computer programs Koza JR (2010), a technique generated from the seminal work of numerous researchers in the 1970s and 1980s, generates possible solutions that fit Manning (1890) and Albert Strickler (1923).

Research involving the GMS equation traditionally focuses on the determination of the roughness coefficient, (n), under different flow regimes (e.g. Ayvaz (2013) and Ding, Jia (2004) and/or for different riverbed materials (e.g. Candela, Noto (2005), as even the presence of biological soil crusts can affect the surface roughness, runoff and erodibility of the channel Rodriguez, Canton (2012).

1.2 Channel Roughness

Channel roughness can be defined as the resistance offered to flow mainly by the bed friction and bed forms. In this study, channel roughness coefficients were identified as parameters by using an automatic optimization method. Channel Roughness and flow estimation from the given flow profile for open channel is an important problem. Ebissa G. K. et al. (2017) identified Channel Roughness as parameter by using optimization method. It is usually parameterized by Manning's n that is imbided in the following flow equation generally termed as Manning's equation.

$$Q = \left(\frac{A}{n}\right) R^{2/3} So^{1/2} \qquad (1)$$

Where, n= Manning's n; A=cross section area of the channel; R=Hydraulic radius; S_o=channel bed slope and Q=discharge in the channel. Manning's n is commonly estimated by applying the strickler's equation that relates n (corresponding to bed material) to the size of course fraction d_{90} or d_{50} of the bed material as follow.

$$n = \frac{(d_{50})^{1/6}}{21.1} \qquad (2)$$

Where, d_{50} is the size of particles in meters which are 50 percent finer. For mixtures of bed material, the above equation is modified as:

$$n = \frac{(d_{90})^{1/6}}{26} \qquad (3)$$

Where, d_{90} is the size of particle in meters and present the particle size in which 90 of the particle is finer than d_{90} (K. Subramanya, 2012).

However, the actual n of a channel may be larger than the strickler's estimate because of additional roughness due to bed forms…etc. The other approach is to monitor the normal depth corresponding to several discharge rates in the channel and to compute n by regressing the Manning equation. This approach provides a composite value of n accounting for all sources of roughness and may work well provided several observations corresponding several discharge rates are available. We can estimate composite roughness (nc) by using the following equation.

$$nc = \frac{(\sum_{i=1}^{N} n_i^{\propto} P_i)^{1/\propto}}{(\sum_{i=1}^{N} P_i)^{1/\propto}} \qquad (4)$$

Where, n_c is composite roughness coefficient; N is total number of segment of wetted perimeter; n_i is roughness coefficient of i^{th} segment; p_i is wetted perimeter of i^{th} segment and $\propto$ is fitting parameter.

However, the underlying assumption of the flow being uniform may not hold. Further, in a typical natural channel with variable roughness along its wetted perimeter, Manning's n may vary with flow depth. The approach of using the uniform flow data does not account for this variability of n. For the present study, d_{50}= 6mm particle size and d_{50} = 20mm particle size are used.

1.3 Brief Review of Literature

Parameter identification techniques have been widely used in the field of hydrology, meteorology, and oceanography. The issue of parameter identification based on the optimal control theories in oceanography can be traced from the early work of Bennett and McIntosh (1982) and Prevost and Salmon (1986). Panchang and O'Brien (1989) carried out early an adjoint parameter identification for bottom drag coefficient in a tidal channel. Das and Lardner (1991) estimated the bottom friction and water depth in a two-dimensional tidal flow. Yeh and Sun (1990) presented an adjoint sensitivity analysis for a groundwater system and identified the parameters in a leaky aquifer system. Wasantha Lal (1995) used singular value decomposition to calibrate the Manning's roughness in one-dimensional (1D) Saint Venant equations. Khatibi et al. (1997) identified the friction parameter in 1D open channel considering the selection of performance function and effect of uncertainty in observed data. Atanov et al. (1999) Used the adjoint equation method to identify a profile of Manning's **n** in an idealized trapezoidal open channel. Ishii (2000) identified a constant Manning's **n** in an open channel flow with a movable bed. Ramesh et al. (2000) solved the inverse problem of identifying the roughness coefficient in a channel network using the sequential quadratic programming algorithm. Sulzer et al. (2002) estimated flood discharges using the Levenberg–Marquardt minimization algorithm. For the parameter identification issues about adjoint methodology in meteorology and oceanography, one may refer to Ghil and Malanotte-Rizzoli (1991) and Zou et al. (1992).

The identifications of parameters in some cases are hard to achieve due to ill-posedness in the inverse problems. Chavent (1974) noted instability and nonuniqueness of identified parameters in the distributed system. Due to the instability, some minimization procedures will lead to serious errors in the identified parameters and make the identification process unstable. In the case of nonuniqueness, the identified parameters will differ according to the initial estimations of the parameters, and not converge to their optimal (or ''true'') values. Yeh (1986) and Navon (1998) have pointed out that the problem of uniqueness in parameter identification is intimately related to identification, which addresses the question of whether it is at all possible to obtain a unique solution of the inverse problem for unknown parameters. Although there are a lot of identification procedures available for estimating parameters in mathematical models, none of them can automatically guarantee stability and uniqueness in the parameter identifications in diverse engineering problems. It is therefore vital to confirm the performance of these procedures to find stable ones that can warrant obtaining the optimal solutions. For the present study, channel roughness is identified by using optimization technique.

Optimization techniques were successfully used by Becker and Yeh (1972, 1972a), Fread and Smith (1978) and Wormleaton and Karmegam (1984) to identify parameters for regular prismatic channels having simple cross-sections. These researchers used the same optimization algorithm (the so-called "Influence Coefficient" Algorithm) which, mathematically, is closely related to both quasi linearization and the gradient method. Khatibi et al. (1997) used a nonlinear least square technique with three types of objective function and identified open channel friction parameters by a modified Gauss-Newton method. Atanov et al. (1999) used Lagrangian multipliers and a least square errors criterion to estimate roughness coefficients. More recently, Ding et al. (2004) used the quasi-Newton method to identify Manning's roughness coefficients in shallow water flows. Nevertheless, the above studies considered only the case of in-bank flow. Therefore, there is a need to extend the method to out-bank flow, where flood plain roughness will obviously have to be considered.

One of the very few studies which dealt with the identification of compound channel flow parameters is the one by Nguyen and Fenton (2005). In this study, roughness coefficients in the main channel and flood plains were identified as two different parameters using an automatic optimization method. The model was applied to Duong River in Vietnam, where roughness coefficients of the main channel and the flood plain were presented as different constant values as well as polynomial functions of stage.

1.4 Objectives

The present study involves estimation of Manning roughness n of a channel having different channel bed materials invoking data of gradual varied flow (GVF). Use of GVF data facilitates estimation of depth dependent Manning's roughness n. the necessary data base was generated by conducting laboratory experiments. The overlying objective is fulfilled through the accomplishment of sub objectives listed below.

1) To identify open channel flow parameters by using Genetic Algorithm optimization Technique
2) To generate and monitor gradually varied flow profiles corresponding to different bed materials, discharge and ponded depths.
3) Invoking the observed data of the GVF profiles and the linked simulation optimization approach to estimates Manning's n corresponding to different channel bed materials in the experimental channel, and hence to calibrate the following composite roughness equation.

$$nc = \frac{\left(\sum_{i=1}^{N} n_i^{\propto} P_i\right)^{1/\propto}}{\left(\sum_{i=1}^{N} P_i\right)^{1/\propto}} \tag{5}$$

Where, n_c is composite roughness coefficient; N is total number of segment of wetted perimeter; n_i is roughness coefficient of i^{th} segment; p_i is wetted perimeter of i^{th} segment and $\propto$ is fitting parameter.

1.6 Methodology

This study was carried out to identify open channel flow parameters by using Genetic Algorithm optimization technique. Manning's roughness coefficient and other parameters are estimated for different bed materials used (d_{50} =6mm and 20mm grain size and Lined concrete bed materials). Also, GVF flow profile is identified. Crank-Nicolson method is used to solve the governing differential equation.

Parameter optimization technique is used to find the optimal value of coefficient roughness for three different bed materials. Estimation of roughness coefficient is based on Manning's equation for estimation of manning roughness coefficient and corresponding manning roughness parameters. This estimation invokes the data of observed GVF profiles and such accounts for different bed materials with the flow depth. Experimental works is done to several sets of data monitored in Hydraulics Laboratory of Civil Engineering Department

2. Literature Review

2.1 General

Resistance to flow depends up on shape, size and density of object placed as an obstacle to offer resistance (Christodoulou, 2014). Effective roughness during overland flow having shallow depth depends on the fraction of flow depth over roughness element height. Also, an inverse relationship is supposed to exit between Manning's n /friction factor f and Froude number (Barros and Colello, 2001). Cylindrical roughness in open channel has been studied and shows that resistance to flow depends up on depth of flow and stem characteristics (Stone et al., 2002). It has been found that spacing as well as size of stripped bed roughness highly influences the flow over a rectangular channel as a free fall (Guo et al., 2008). Gravel bed roughness is conventionally given by grain size. A new approach was adopted to measure the resistance of flow due to gravel bed by a new parameter based a characteristics of elevation field (Qin and Leung Ng, 2012).

2.1 Estimation of Manning's n

Genetic programming (GP – an extension of genetic algorithms to the domain of computer programs Koza JR (2010), a technique generated from the seminal work of numerous researchers in the 1970s and 1980s, generates possible solutions that fit the data given an evaluation metric. The adaptation of these solutions to the data is akin to the biological adaptation of an individual member of a population to an environment.

On the other hand, open-channel hydraulics' (OCH) applied research often links empirical formulas to observational data (e.g. Weisbach (1845), St. Venant (1851), Neville (1860), Darcy and Bazin (1865)). For example, the Manning formula, also known as the Gauckler-Manning-Strickler formula (here after GMS), is an empirical formula for open-channel flow, or free surface flow driven by gravity. The formula is attributed to the engineers Philippe Gauckler (1967), Robert Manning (1890) and Albert Strickler (1923). The formula (1) relates the cross-sectional average velocity ($V = Q/A$), the hydraulic radius (R), and the slope of the water surface (S), with a friction coefficient n, characteristic of the channel's surface.

$$V = \left(\frac{1}{n}\right) R^{2/3} S^{\frac{1}{2}} \tag{6}$$

Where, V is the cross-sectional average velocity in m/s, n is a non-dimensional roughness coefficient, R is the hydraulic radius (m), and S is the slope of the water surface (m/m). The relationship can be used to calculate the discharge (Q) if we substitute V in (1) by Q/A, obtaining:

$$Q = \left(\frac{A}{n}\right) R^{2/3} S^{\frac{1}{2}} \tag{7}$$

Research involving the GMS equation traditionally focuses on the determination of the roughness coefficient, (n), under different flow regimes (e.g. Ayvaz (2013) and Ding, Jia (2004) and/or for different riverbed materials (e.g. Candela, Noto (2005), as even the presence of biological soil crusts can affect the surface roughness, runoff and erodibility of the channel Rodriguez, Canton (2012).

Manning's equation is conveniently used to compute discharge rates or velocity of flow in open channel problems. Except the value of roughness coefficient all other parameter in the equation can be easily measured. The uncertainty in the estimation of appropriate value of n is the most difficult task faced while application of the equation. Experiments for computation of Manning's n where conducted on twenty-one steep slope streams in Colorado which suggested following relationships of manning's n i.e. value of n decreases with increase in depth of flow, n decreases with decrease in gradient and streams are found to be in supercritical condition which corrected the prior conception of subcritical condition (Jarret, 1984). A numerical method was proposed in order to evaluate Manning's n of shallow water flows (Ding et al., 2004) and an equation is developed to predict Manning's n for high gradient streams (Jarret, 1984). It has been found that Manning's equation is effectively applicable in furrow irrigation problems and Manning's n varies for low discharge rates but attain a constant value at high discharge rates (Esfandiari and Maheshwari, 1998). Nonetheless, computation of Manning's roughness coefficient for border irrigation was also described (Li and Zhang, 2001). The behavior of Manning's n was studied for erodible and non-erodible soils and it has been found that n value is a function of gradient for erodible soils only (Hessel, 2003). Variation of Manning's n with space and time for cropped furrow as well as bare furrow was studied (Maillapalli et al., 2008). A potentially applicable model was developed for estimation of channel roughness which uses embeds finite difference approximation of governing equation to an optimizer having inputs as depth of flow and rates varying with time and space (Ramesh et al.,2000). Apart from experimental data and numerical models, n is also estimated by using software based simulation models. HEC- RAS model is used for roughness coefficient for Hilla River (Hameed and Ali, 2012).

2.2 Composite Roughness

Multi roughness channels are not uncommon in field application of open channel flow hydraulics. Due to different roughness of wetted perimeter the overall roughness of the channel is given by composite roughness. Composite roughness comprises of individual roughness effect of channel cross section. Seventeen different equations based on several assumptions along with six different techniques to sub divide the channel cross section were given by numerous investigators (Yen, 2002). The credibility of these equations would be assessed by employing experimental data. An effective methodology has been proposed to evaluate optimal design of cross sectional area of a channel having composite roughness using Manning's roughness equation (Das, 2000).

3. Experimental Works

3.1 Introduction

In this chapter, water surface flow profiles corresponding to specific discharges, bed material and ponded depth have been obtained through experimentation. This chapter includes a detailed description of experimental setup, adopted procedures and the observations with range of data obtained for different flow conditions. The experiments for the investigation were carried out in Hydraulics Laboratory of Civil Engineering Department. IIT-Roorkee, India

3.2 Details of Experimental Setup

3.2.1 Flume

A rectangular tilting flume of length 30m, width 0.205m and height 0.50m was used (fig 3.1). The bed of the flume was made up of lined concrete and the other two sides were made up of glass and GI sheet. Discharge was released through an inlet pipe of 0.010m diameter into the flume. The entrance of the channel was provided with flow suppressors in order to make the flow stable. In order to maintain desired depth of water at the downstream of the channel, a tail gate was fitted at the end of the channel. Water discharging from the tail gate, passed to the sump which was circulated again through a 15hp centrifugal pump for further experimentation.

3.2.2 Experimental Procedures

The experiments were conducting by adopting the following steps as mentioned below:-

3.2.2.1 Slope Measurement

All the sets of experiment were performed on a particular slope of the channel. The slope was measured by using two steel containers connected with a long rubber tube. Both the containers were placed on the channel bed separated by the rubber tube along the length of the channel. One of the containers placed at higher elevation was filled with water and simultaneously care was taken to remove air bubble from the connecting tube. They are left undisturbed for sufficient amount of time around 24 hours. Then the water levels were measured. The slope of the channel was computed by using the following formula.

$$S_o = \frac{H_1 - H_2}{L} \quad (8)$$

Where, H_2 and H_1 is the depth of water in second and first container respectively after equilibrium is established and L is the distance between the containers.

3.2.2.2 Sieve Analysis

Sieve analysis was performed to determine the particle size of the material used to create artificial bed roughness. Results of sieve analysis were plotted to investigate the particle size of the bed material used in the present study. Experiments were conducted on two different bed materials. First on one rough bed condition having gravel as a bed particle size d_{50} =20mm, d_{50}=6mm and then on the smooth condition having lined concrete as bed material.

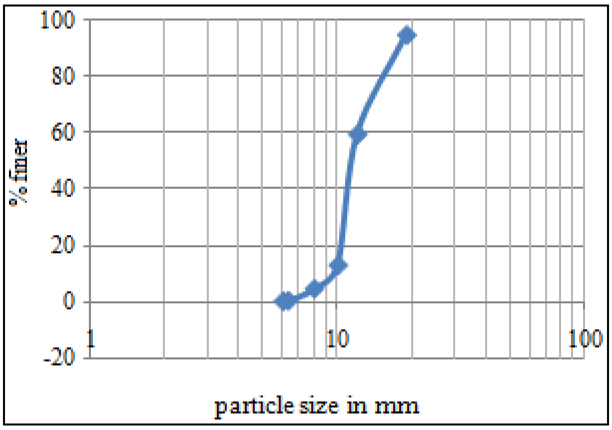

Figure 1: Gradation curve for d_{50}=20mm

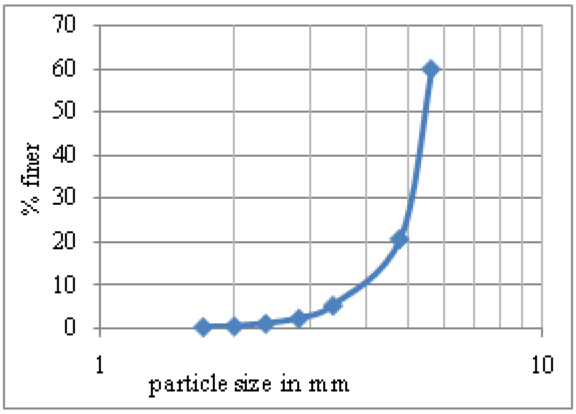

Figure 2: Gradation curve for d_{50}=6mm

3.2.2.3 Calibration of orifice meter

Orifice meter was provided in the inlet pipe for the measurement of discharge. Orifice plate was made up of GI sheet having diameter of 0.06m and the diameter of inlet pipe was 0.10m. Ultrasonic flow meter was used for the calibration of coefficient of discharge of orifice meter. Different discharges were noted corresponding to varying head. This result was plotted and the best fitted line was used (Fig. 3.6).

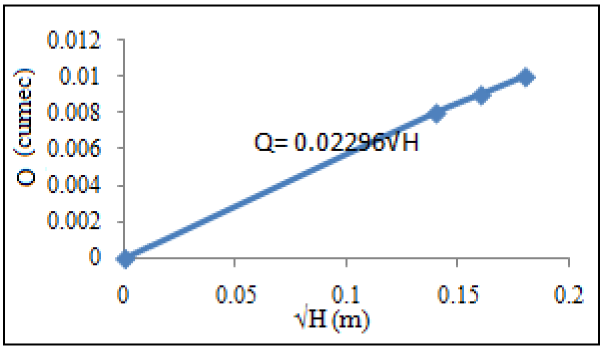

Figure 3: Calibration curve

Cd was calibrated as 0.66. after calibration of Cd of orifice meter, the discharge in the channel was computed by using the following equation.

$$Q = C_d a_o \sqrt{2gh} \quad (9)$$

Where, a_o is area of orifice plate; g= acceleration due to gravity and h= height of water column.

3.2.2.4 Measurement of water surface profiles

1) Water was released into the rectangular flume by opening the valve of inlet pipe.
2) The desired depth of flow was maintained at the downstream end by operating sluice gate provided at the end of the channel. The depth of water was measured using pointer gauge.
3) After a while when the flow become steady in the channel and the desired depth was maintained at the downstream end, the water surface profile was being measured.
4) Starting from the maintained depth at the downstream end (0.00m), the water surface profile is measured towards upstream at ten (21) discrete locations that are 0.00m, 0.20m, 0.70m, 1.20m, 1.70m, 2.20m, 2.70m, 3.70m, 4.70m, 5.70m, 6.70m, 7.70m, 8.70m, 9.70m, 10.70m, 12.70m, 14.70m, 16.70m, 18.70m, 20.70m and 22.70m.
5) The above mentioned steps were repeated for thee different downstream depths, Discharges rates and bed roughness as mentioned in Table 1

Table 1: Data used for experimental measurement of water surface profiles

Discharge rates (m^3/s)	8.601×10^{-3}	9.233×10^{-3}	9.314×10^{-3}
Downstream depths (m)	0.25	0.30	0.35
Bed materials (d_{50} in mm)	d_5=20	d_{50}=6	Lined concrete

4. Results and Discussion

4.1 Model Formulation

The present study involves generation of the GVF data that are subsequently employed for estimation of Manning's n corresponding to different segment of wetted perimeter (Fig 4.2) in the experimental channel. The estimation also involves calibration of the following composite roughness n_c equation.

$$nc = \frac{\left(\sum_{i=1}^{N} n_i^{\alpha} P_i\right)^{1/\alpha}}{\left(\sum_{i=1}^{N} P_i\right)^{1/\alpha}} \quad (10)$$

Where, n_c is composite roughness coefficient; N is total number of segment of wetted perimeter; n_i is roughness coefficient of i^{th} segment; p_i is wetted perimeter of i^{th} segment and $\propto$ is fitting parameter.

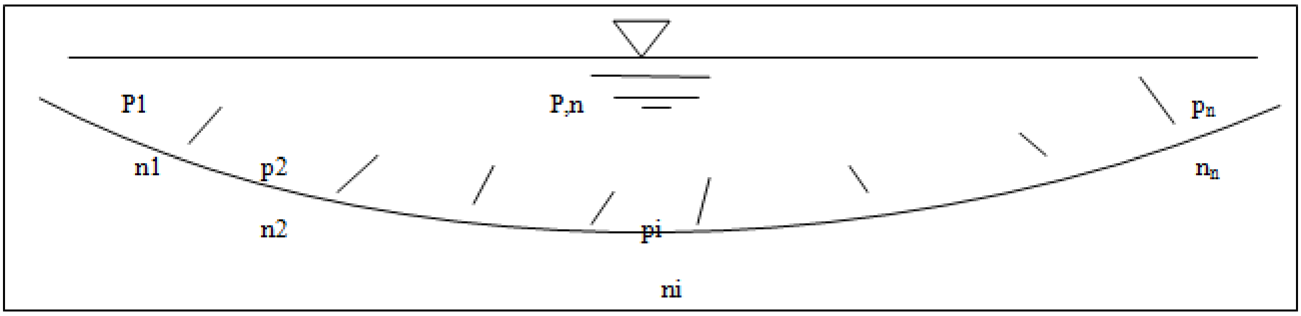

Figure 4: Multi-roughness channel

The monitored GVF data comprises the depths measured at finite number of discrete locations corresponding to several downstream heads and discharge rates (Fig. 4.3). The data base is thus enumerated as follow:
$[\{(\hat{y}_{ikl}, i = 1, \ldots, M_1), k = 1, \ldots \ldots M_2\}, l = 1, \ldots, M_3];$
$(Q_k, k = 1, \ldots \ldots M_2); (H_l, l = 1, \ldots \ldots M_3)$

Where M_1 is the number of discrete sections at which the GVF depths are measured; M_2 is number of discharge rates for which the GVF depths are measured and M_3 is number of downstream heads maintained at the tail gate during the measurement of GVF depths.

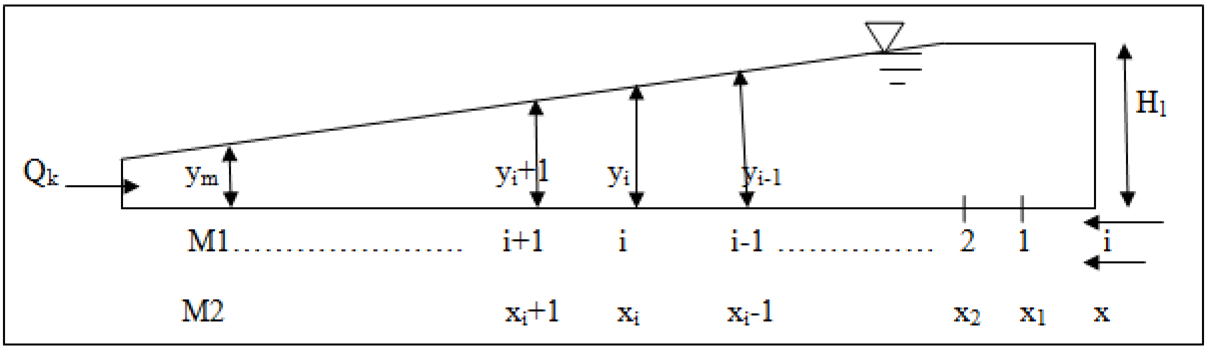

Figure 5: Measured GVF data

Invoking this data base, the problem of roughness estimation is posed as the following optimization problem.

Decision Variables:
$(n_i, i = 1, \ldots \ldots N)$ and $\propto$

Objective function:
The objective function is designed to arrive at such values of decision variables that permit minimized mismatch between the observed and the computed GVF profiles. The mismatch is qualified in terms of the following data observed during the experiments.

$$Min\ Z = \sum_{l}^{M3} \sum_{k}^{M2} \sum_{i}^{M1} w_i \left[y(x_i, Q_k, H_l) - \hat{y}_{ikl}\right]^2 \quad (11)$$

Where, $w_i = \frac{(x_{i+1} - x_{i-1})}{2}$, $y(x_i, Q_k, H_l\ and\ \hat{y}_{ikl}$ are simulated and experimentally measured depth at i^{th} discrete section, k^{th} discharge rate and l^{th} downstream head maintained at the tail gate respectively.

Constraint:

$$nmax_i \geq nmin_i, i = 1, \ldots \ldots N \quad (12)$$

$$2 \geq \propto \geq 1 \quad (13)$$

Where, $nmax_i$ = upper limit of n_i and $nmin_i$ = lower limit of n_i.

4.1.1 Optimization

The following problem was solved three times corresponding to different bed conditions i.e. d_{50}=20mm, d_{50}=6mm and lined concrete as bed materials.

Decision Variables:
$(n_i, i = 1, \ldots \ldots 3)$; and $\propto$

Objective Function:

$$Min\ Z = \sum_{l}^{3} \sum_{k}^{3} \sum_{i}^{M} w_i \left[y(x_i, Q_k, H_l) - \hat{y}_{ikl}\right]^2 \quad (14)$$

Where, $y(x_i, Q_k, H_l)$ and $\hat{y}_{ikl}$ are simulated and experimentally measured depth at i^{th} discrete section, k^{th} discharge rate and l^{th} downstream head respectively; M is a subset of the locations where the observed depth is larger than 1.01 x normal depth; w_i is the weight assigned to the mismatch at i^{th} location. In the present study the weights are assigned to index the length discretized by the discrete sections. Thus (w_i) is defined as follows:

$$w_i = \frac{(x_{i+1} - x_{i-1})}{2} \quad (15)$$

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Constraint:

i) Following six constraints were assigned to impose upper and lower limits of the segment roughness coefficients $nmax_i$ and $nmin_i, i = 1, \ldots.3$).

$$nmax_i \geq nmin_i, i = 1, \ldots.3 \qquad (16)$$

The adopted values of the limits are given in Table 2

Table 2: Upper and lower limits of roughness coefficients

	n_1	n_2	n_3
$nmax_i$	0.1	0.1	0.1
$nmin_i$	0.001	0.001	0.001

ii) Following three constraints were assigned to ensure realistic relative roughness of the three roughness coefficients.

$$n_1 \geq n_2 \geq n_3 \qquad (17)$$

iii) Following constraints was assigned to impose upper and limits of fitting parameters ($\propto$).

$$2 \geq \propto \geq 1 \qquad (18)$$

Since the reported value of $\propto$ 1.5, a range of 1 to 2 was prescribed.

Linked simulation optimization approach is used to estimate the optimal values of the parameters for three bed conditions i.e. d_{50}=20mm, d_{50}=6mm and lined concrete as bed materials and their corresponding GVF profiles were simulated.

4.1.2 Optimal values

Optimal values of decision variables and their corresponding minimized objective function value for different bed materials are mentioned in Table 3.

Table 3: Optimal values of decision variables and objective function

Bed materials	n_1	n_2	n_2	$\propto$	$Min\ Z\ (m^2)$
d_{50}=20mm	0.034	0.016	0.018	1.42	1.16×10^{-4}
d_{50}=6mm	0.030	0.016	0.018	1.46	1.62×10^{-4}
Lined concrete	0.027	0.015	0.017	1.48	1.09×10^{-4}

4.1.3 Optimal reproduction of GVF profiles

Computed GVF profiles corresponding to the optimal parameter values and the variation of composite roughness are in the following figures. The profile is plotted for three different bed materials corresponding to discharge rates and water depth.

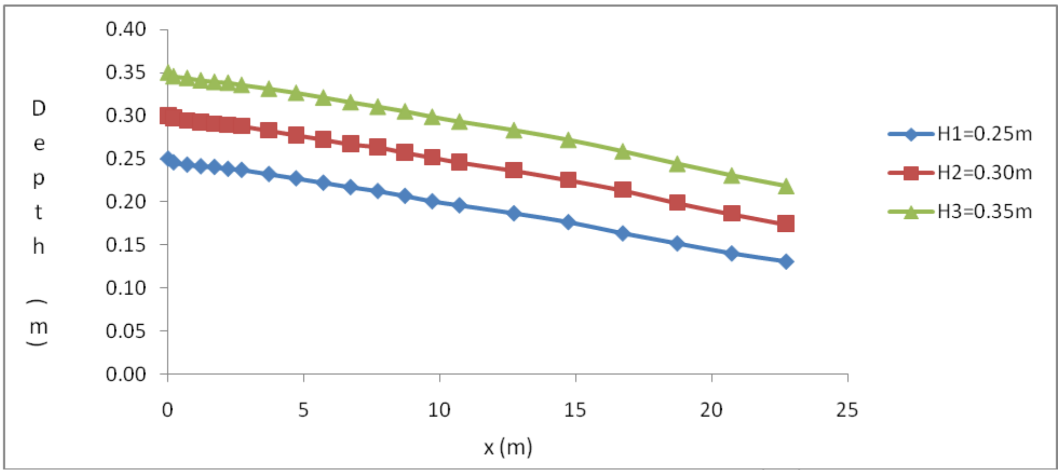

Figure 6: Observed reproduction of GVF profiles (Q=8.601×10^{-3} m^3/s and d_{50}=20mm)

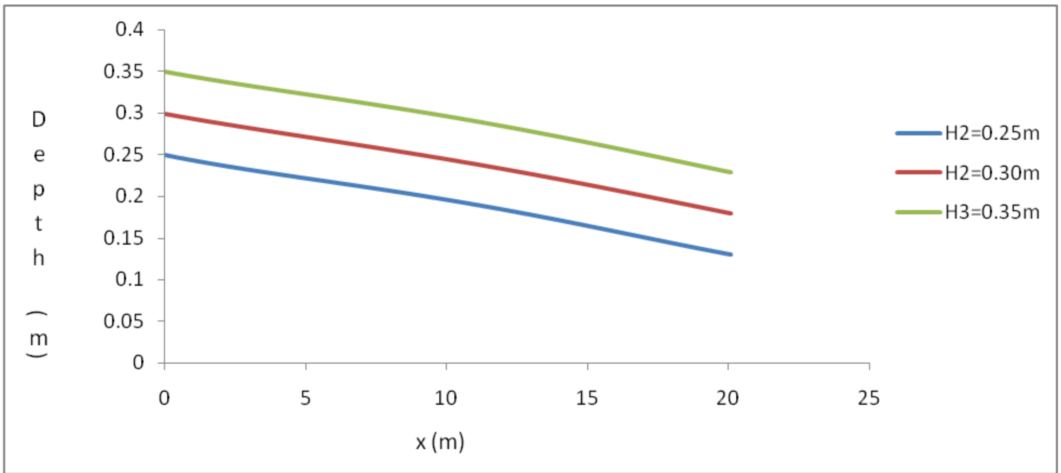

Figure 7: Optimal reproduction of GVF profiles (Q=8.601×10^{-3} m^3/s and d_{50}=20mm)

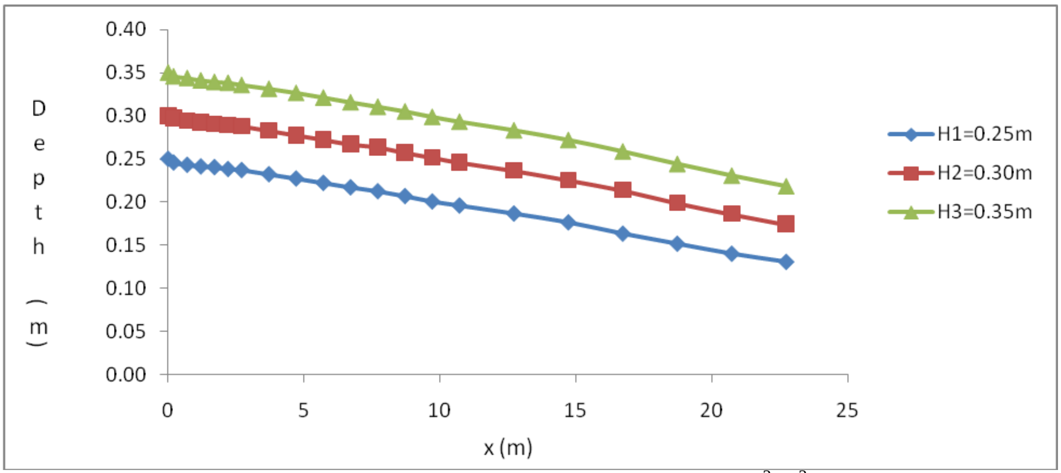

Figure 8: Observed reproduction of GVF profiles (Q=9.233x10^{-3} m^3/s and d_{50}=6mm)

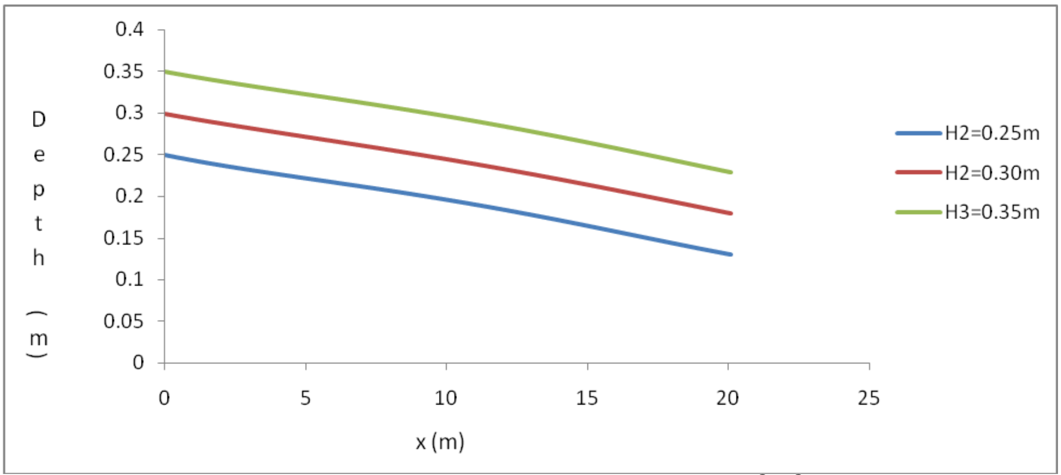

Figure 9: Optimal reproduction of GVF profiles (Q=9.233x10^{-3} m^3/s and d_{50}=6mm)

4.2 Discussion of Results

4.2.1 Estimated parameters

The bed roughness (n_1) varies from 0.026 to 0.033 as bed material /condition changes from lined concrete to gravel (d_{50}=20mm). The corresponding reported/ Strickler's estimates are given in Table 4 by using equation 2. It may be seen that optimal roughness estimates are higher than Strickler's estimates.

Table 4: Reported/Strickler's estimated optimal estimates for bed materials

Bed material/condition	Reported/Strickler's Estimation	Optimal estimates
d_{50}=20mm	0.0247	0.034
d_{50}=6mm	0.0202	0.030
Lined concrete	0.013-0.015	0.027

The roughness coefficient of glass and GI sheet sides as optimized for various runs are presented in Table 5.

Table 5: Reported/Strickler's estimates and optimal estimates for sides

side \ d_{50}	d_{50}=20mm	d_{50}=6mm	Lined concrete	Tabulated values
Glass	0.016	0.016	0.015	0.010
GI sheet	0.018	0.018	0.017	0.012

The estimated roughness coefficients satisfy the known inequality (n_2 < n_3) and are higher than the tabulated values. This establishes the credibility of the proposed model. The optimal value of $\propto$ (fitting parameter) ranges from 1.42 to 1.48, which differs from the reported value i.e. 1.5. The optimal value of $\propto$ increases as the bed materials get finer.

4.2.2 Reproduction of observed profile

Computed GVF profiles corresponding to the optimal parameter values match quite well with corresponding observed profiles.

4.2.3 Variability of composite roughness

It can be observed that composite roughness reduces with increase in flow depth. Apparently because of increase in weightage of side resistance, the value of composite roughness increase.

5. Conclusion

This study was carried out to identify open channel flow parameters. Manning's roughness coefficient and other parameters are estimated for different bed materials used (

d_{50} =20mm grain size , 6mm grain size particles and Lined concrete bed materials). Also, based on the estimated value of Manning roughness coefficient and flow depths, GVF flow profile is identified.

An optimization method is applied to identify the parameters based on Manning formula for estimation of manning roughness coefficient and corresponding manning roughness parameters. This estimation invokes the data of observed GVF profiles and such accounts for different bed materials with the flow depth.

Experimental works is done to several sets of data monitored in Hydraulics Laboratory of Civil Engineering Department. The application led to the following conclusions;

i) The GVF profile computed on the basis of estimated parameters match quite closely with the corresponding observed profiles.
ii) Strickler's formula under estimate the roughness due to the bed material.
iii) The following commonly used formula is calibrated for Manning coefficient estimation

$$nc = \frac{\left(\sum_{i=1}^{N} n_i^{\propto} P_i\right)^{1/\propto}}{\left(\sum_{i=1}^{N} P_i\right)^{1/\propto}}$$

iv) The currently documented value of $\propto$ is 1.5. However, the present work reveals that it varies from 1.43 to 1.47. The value of $\propto$ generally decreases as the bed material gets coarser.

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