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Optimal Prediction of Lateral velocity distribution in compound channels

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Abstract

Many rivers have deep main channels in the center with one or two adjoining floodplains. Prediction of the lateral velocity distributions over the entire river cross-section is necessary for solving many river-related and hydro-engineering problems. Using Genetic Algorithm (GA), this paper proposes a simple model with two separate equations for predicting the lateral velocity distribution in the main channel and floodplains of straight compound channels. The proposed model is based on two key parameters of compound channels, i.e. depth ratio and the coherence parameter. The constants and exponents of the model are obtained by using a GA based on both experimental data of several compound flumes and measurements of the river Severn in the UK. Using several statistical measures, it is shown that the predictions of lateral velocity distribution and stage-discharge by the model agree well with the observed laboratory data and natural river measurements used for calibration and validation. Moreover, the model is shown to outperform the conventional vertical divided channel method with 11.2 % less error on average in predicting the velocity distribution.

Keywords: Coherence parameter, Compound channels, Genetic algorithm, Lateral velocity.

1. Introduction

In open channel flow, lateral velocity distribution models have become the subject of analysis and application in recent years (Weber and Menendez, 2004). Lateral velocity distributions are required for solving many hydro-engineering problems such as development of stage-discharge curves and estimation of boundary shear stress distribution (Guan, 2003; Tang and Knight, 2009b), identification of erosion or deposition within a reach section of a river, computation of sediment transport capacities (Hu et al, 2010), selection of proper locations for river intakes, river-bank protection designs, prediction of scour depth at bridge piers and abutments (Kouchakzadeh and Townsend, 2000), and computing of the lateral change of bed form across the river (Seo and Gadarlab, 1999). The lateral velocity distribution can be directly utilized to develop river stage-discharge curves, which are one of the main concerns of researchers in both simple and compound river channels, as they play a very important role in river training and flood control works (Knight et al, 2010). In natural rivers, to obtain reliable stage-discharge curves, stream-wise lateral velocity distribution is measured periodically in both low and high flows, which is costly and time consuming. On the other hand, for compound river channels with wide floodplains, in high flood events, measuring velocity across the river is difficult and often dangerous. Therefore, new simple accurate methods are required for predicting lateral velocity distribution in rivers, especially in flood conditions.

In a flood event, a river often has a compound section, consisting of both the main channel and floodplains, and its hydraulic features are significantly different from a simple cross-section channel. In simple channels, the Manning's equation has acceptable accuracy for flow discharge computations (Knight et al. 2010). In compound channels, however, due to significant differences of flow depth and Manning's roughness coefficients between the main channel and the floodplains, each subsection has a different velocity, that subsequently causes a strong momentum exchange between the main channel and the floodplains, as seen in Fig. 1.

<div align="center">a)</div> <div align="center">b)</div>
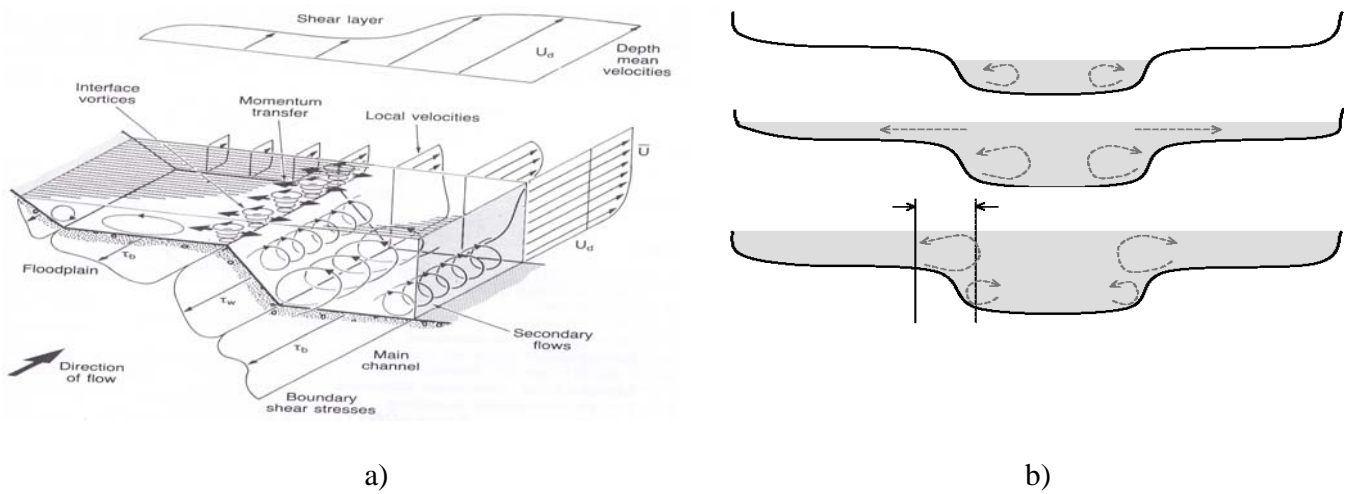
Fig. 1. Mechanism of overbank flow in a straight compound channel, a) turbulence structure and momentum exchange (Knight and Shiono, 1991), b) development of shear layer between main channel and floodplain

The shear layer, generated between the main channel and the floodplain, can considerably affect the lateral velocity distribution. This layer extends towards both floodplain and main channel zones. The extent of this layer depends on geometric and hydraulic conditions (e.g. aspect ratio, width ratio, relative depth and velocity difference between the main channel and the floodplain). The quantification of shear layer width in a compound channel is quite ambiguous because no exact definition or formula is available in the literature (Mohanty et al, 2011).

Due to the velocity difference between the main channel and the floodplain in a compound channel, many enhanced 1D and 2D hydrodynamic models have been proposed to take into account the flow interaction between the main channel and its floodplains (e.g. Shiono and Knight, 1991; Ackers, 1992; Bousmar and Zech, 1999; Ervine et al., 2000; Tang and Knight, 2009a). Some of these methods have promising results, but most of them have complex procedures and rely on some empirical parameters which limit their wide applications in river modelling.

Since the 1990's, several quasi-2D mathematical models have been developed for obtaining lateral velocity distribution in compound channels. These models are known as Lateral Distribution Models (LDM) (Shiono and Knight, 1991; Wark et al. 1994; Ervine et al. 2000; Tang and Knight, 2008, 2009a; Hu et al. 2010). Despite showing promising predictions, due to their complexity and some limitations in their assumptions, applying these models is generally not straightforward, and could cause difficulties for hydraulic engineers. Furthermore, these models require the use of numerical methods for solving the governing differential equations and the integration of obtained lateral velocity distribution for flow discharge computations, which introduce some numerical errors.

Among the velocity lateral distribution models, the Shiono and Knight Model (SKM) is more popular with widespread applications (Unal et al, 2010). This model takes the following form of an ordinary differential equation:

$$\rho g H S_0 - \rho \frac{f}{8} u_d{}^2 \sqrt{1+s^2} + \frac{\partial}{\partial y}\left\{\rho \lambda H^2 \left(\frac{f}{8}\right)^{1/2} u_d \frac{\partial u_d}{\partial y}\right\} = \beta_s \, \rho g S_0 H \qquad (1)$$

where ρ =density of water, g= gravity acceleration, H=local flow depth, S_0=longitudinal bed slope, f =Darci-Wiscbach friction factor, u_d =depth-mean stream-wise velocity, s=side slope of main channel or floodplains, y=lateral distance, λ=dimensionless eddy viscosity coefficient, and β_s= a calibration constant for secondary flow term. For complex compound river channels, solving Eq. 1 isn't straightforward and is often solved by numerical methods. SKM is a Reynolds-averaged Navier–Stokes (RANS) model that uses three different calibration coefficients, namely, friction, f, dimensionless eddy viscosity, λ, and secondary flow parameters, for predicting lateral distribution of depth-mean velocity. Determining these coefficients in natural channels is not always feasible and requires some experiences (Knight et al. 2010). To overcome this difficulty, Sharifi (2009) applied GA for the calibration of SKM coefficients.

To simplify the hydraulic computations of compound channels, some less complex approaches have also been proposed for predicting the total discharge in compound channels. MacLeod (1997) developed an Artificial Neural Network (ANN) functional approximator for predicting the discharge capacity of uniform meandering compound channels. By testing the ANN method against the data from the UK FCF Series B program, MacLeod (1997) demonstrated that this method gives more accurate discharge predictions than the traditional methods for the majority of available flow data sets. Liu and James (2000) used artificial neural networks to predict conveyance capacity in meandering compound channels. Their model predicts a dimensionless discharge based on main channel and floodplain flow depths, vegetation density over the cross section, channel sinuosity, transverse floodplain slope, and floodplain bend tightness. The model was trained using 45 data sets representing a wide range of main channel and floodplain characteristics and tested using 15 additional data sets. The discharge prediction error was -0.19% on average for all the data used in development and testing of the model, where only one case had a large error of 15%. Unal et al. (2010) applied a multilayer perception neural network (MLP) with Levenberg-Marquardt algorithm for flow discharge prediction in straight compound channels. They compared their results with the single-channel method (SCM), the divided-channel method (DCM), the coherence method (COHM), the exchange discharge method (EDM) and the Shiono-Knight method (SKM). They found that the ANN model gives better statistical results than the existing 1D and 2D approaches. Azamathulla and Zahiri (2012) proposed a simple dimensionless equation for stage-discharge relationship prediction of straight compound channels using linear genetic programming (LGP). They used a large data set of field and laboratory flumes of 30 compound channels in the study. Their results indicated better performance of the proposed equation compared with the traditional DCM method. Zahiri and Azamathulla (2014) used the gene-expression programming (GEP) and decision tree models (M5) for calculation of stage-discharge curve in field

and laboratory compound channels. They found that both LGP and M5 have considerable accuracy for prediction of flow discharge, but the LGP model performs better from the statistical point of view.

All the above mentioned optimization based studies focus exclusively on predicting the total discharge. However, there are limited investigations regarding lateral distribution of flow velocity across compound channels. Using Genetic Programming (GP), Harris et al. (2003) developed two dimensionless expressions for lateral distributions of depth-mean velocity in main channels and floodplains for vegetated compound channels. The results for the compound channel flumes were found to be encouraging. Due to the large number of parameters (nine parameters) used in their expressions, as well as the certain degree of scattering in floodplain results, these expressions may have some limitations in field applications.

Due to the importance of transverse distribution of stream-wise velocity in flooded rivers and the difficulties and complexity of applying LDM methods, this paper has proposed simple, fast and accurate equations for predicting lateral velocity distribution in compound channels with the coefficients of equation being optimized by Genetic Algorithm (GA). Two separate dimensionless equations have been developed for the main channel and the floodplain, respectively. The new proposed equations have been successfully applied for both flume data and field data of a compound river section (River Severn at Montford Bridge, UK). In addition, the proposed method has the advantages of being easy to use and requiring less computation for obtaining the velocity distribution across compound channels.

2. Background

Coherence Parameter

In a compound channel, the simple sub-division and composite roughness approaches are not appropriate for predicting channel discharge (or conveyance) (Ackers, 1992; Myers and Lyness, 1997). These approaches either over- or under-estimate the channel discharge since they do not take into account the interactive effects between the main channel and the floodplains. The degree of interaction will affect the discharge distribution between main channel and floodplains depending on many factors, including relative depth of floodplain flow to main channel flow, width ratio between main channel and floodplain, relative roughness of floodplain to main channel, and channel geometry. Based on the high quality data of compound channel of the UK Flood Channel Facility (UK-FCF) flume (Knight and Sellin, 1987), Ackers (1992, 1993) introduced an important non-dimensional parameter, defined as the coherence parameter (COH), for hydraulic analysis of compound open channels. COH is defined as the ratio of the basic conveyance (calculated by treating the compound channel as a single unit) to that computed by the traditional vertical divided channel method which is widely used in 1D hydraulic engineering software such as HEC-RAS, ISIS, MIKE11 and SOBEK (Huthouff et al, 2008). The coherence parameter (*COH*) is expressed as (Ackers, 1992, 1993):

$$COH = \frac{A^{5/3} \Big/ \left(\sum_{i=1}^{N} n_i^{1.5} P_i \right)^{2/3}}{\sum_{i=1}^{N} \frac{1}{n_i} \frac{A_i^{5/3}}{P_i^{2/3}}} \qquad (2)$$

where subscript *i* refers to subsection (main channels or floodplains), P_i , A_i , n_i are the wetted perimeter, the area, and Manning's roughness coefficient of each subsection, respectively, A is the total cross-sectional area of the channel, and N is the number of subsections. The closer to unity the COH parameter, the more appropriate it is to treat the channel as a single unit. As indicated by Eq. (2), COH

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considers the channel geometry and hydraulic roughness. The coherence approach has now been established as one of the useful 1D approaches for compound channel flows (Atabay and Knight, 2006).

Genetic Algorithm

Genetic Algorithms (GA) are a family of computational models inspired by Darwin's natural evolution which states that the survival of an organism is affected by the rule of "survival of the strongest species". These algorithms encode a potential solution to a specific problem on a simple chromosome-like data structure and apply recombination operators to these structures to preserve critical information. Genetic algorithms are often viewed as function optimizers, although the range of problems to which genetic algorithms have been applied is quite broad (Whitley, 1991).

A solution generated by genetic algorithm is called a chromosome, while a collection of chromosomes is referred to as a population. A chromosome is composed from genes and its value can be either numerical, binary, symbols or characters depending on the problem to be solved. These chromosomes will be evaluated by a fitness function that measures the suitability of the solution generated by GA. Some of the chromosomes in the population will mate through a process called crossover, thus producing new chromosomes named offspring which its genes composition are the combination of its parents. In a generation, a few chromosomes will have mutation in their genes. The number of chromosomes which will undergo crossover and mutation is controlled by a crossover rate and a mutation rate parameter. Chromosomes in the population that will maintain for the next generation will be selected based on Darwinian evolution rule, i.e. the chromosome which has higher fitness value will have greater probability of being selected again in the next generation. After several generations, the chromosome value will converge to a certain value which is the best solution for the problem.

The general GA process can be summarized as continuously moving from one population of candidate solutions (chromosomes) to a new population of fitter solutions using a kind of natural selection together with the genetic operators of crossover and mutation (Mitchell, 1999). This cycle of evaluation–selection–reproduction is continued until an optimal or a near-optimal solution is found (Goldberg, 1989; Michaelwicz, 1992).

It should be noted that most soft computing techniques [e.g. ANNs, Support Vector Machines (SVM)] may provide very good approximations of experimental data, but practitioners who wish to apply these approximations to solve related problems cannot use the techniques because they may not have access to the trained models of these soft computing techniques. GA and its family of models (e.g. GP and GEP), on the other hand, result in mathematical or symbolic expressions that can be readily applied by anyone. Furthermore, GA and GP may be more powerful than neural networks and other machine learning techniques, and be able to solve problems in a wider range of disciplines (Koza, 1992).

3. Proposed Method

In the proposed method, at first, the cross section is subdivided into a number of small elements or slices. Then computational nodes are specified on the element's boundaries for calculation of lateral velocity distribution, as seen Fig. 2 for a river compound channel, where B is the total water surface width, b_c is the bottom width of channel, h is the bankfull depth, b_f is the width of the floodplain, and H is the flow depth.
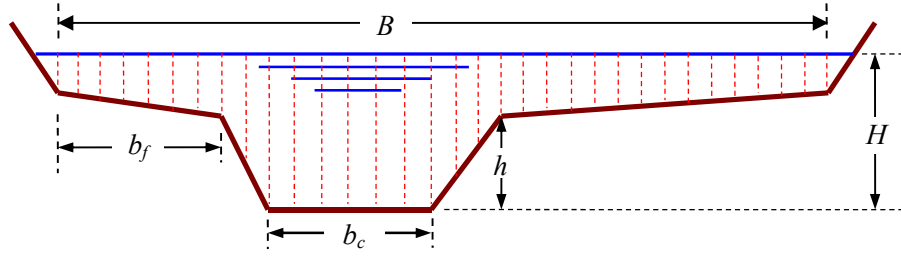
Fig. 2. Division of compound cross section into small vertical elements for velocity lateral distribution

In this approach, the lateral velocity distribution in the main channel and the floodplain is calculated based on Manning's equation by two dimensionless parameters, i.e. relative depth (Dr) (i.e. ratio of water depth in floodplain to that of main channel, (H-h)/H) and coherence parameter (COH), which are known to be important flow parameters for the analysis of compound channels (Ackers, 1992, 1993). Accordingly, a new simple equation is used to estimate the velocity at each element:

$$\frac{u_i}{u_{iMan}} = Dr^a COH^b \tag{3}$$

where Dr is the relative depth, and a and b are two calibration variables. u_i and u_{iMan} are the depth-averaged velocity and the velocity obtained from Manning's equation, at the center of each vertical element, respectively. The Manning's velocity is computed by the following equation:

$$u_{iMan} = \frac{1}{n_i} R_i^{2/3} S_0^{1/2} \tag{4}$$

where R is hydraulic radius.

It should be noted that Eq. (3) is somewhat similar to the approach of Ackers (1992, 1993), who used COH and Dr parameters to modify flow discharge of compound channels based on the conventional vertical divided channel method which relies on the Manning equation. In the presented approach, the two variables a and b, will be obtained by optimization based on experimental data of compound channels.

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It is expected that exponents *a* and *b* in Eq. (3) will have different values in the two subsections due to strong momentum exchange between the main channel and the floodplain. Furthermore, since *a* is an exponent to the relative depth, which does not directly link to the channels' characteristics (e.g. roughness, channel width), it may be considered as a constant value for both main channel and floodplains. However, *b* is an exponent of coherence parameter, which is relatively more sensitive to the geometric and hydraulic parameters compared with exponent *a,* and hence *b* is considered as a function of channel characteristics, such as channel geometry and hydraulic features:

$$b = \alpha Dr^{\beta} \left(\frac{h_f}{h} \right)^{\gamma} \left(\frac{n_f}{n_c} \right)^{\theta} \left(\frac{b_f}{B/2} \right)^{\eta} \tag{5}$$

where h_f is the flow depth of floodplain (*H-h*), n_c and n_f are Manning's roughness in main channel and floodplain, respectively, and α, β, γ, θ and η are calibration variables.

The sum of squared errors between the observed and predicted values of depth-averaged velocities was selected as the object function:

$$f(z) = Min \sum_{i=1}^{N} (X - Y)^2 \tag{6}$$

where *X* and *Y* are the observed and predicted values of depth-averaged velocities, respectively, and *N* is the total number of vertical slices across the compound section. Genetic algorithm (GA) is used to perform this minimization and determine the optimum values for exponents *a* and *b* in Eq.(3).

4. Data Set

For determining the optimum values of exponents *a* and *b* in Eq. (3), the well-known high quality compound channel data of the UK-FCF flumes (FCF, Series 01, 02, 06 and 07) (Knight and Sellin, 1987, www.flowdata.bham.ac.uk) were selected for calibration and validation. Furthermore, two

experimental tests from Guan (2003) were used for verification, in addition to field data from River Severn at Montford Bridge (Knight et al. 1989). The data sets are summarized in Table 1.

Table 1. Overview of data sets used for model calibration and verification

	Calibration			Verification		
	FCF02	FCF06	FCF07	FCF01	Guan (2003)	River Severn
Main channel bed width, b_c (m)	1.5	1.5	1.5	1.5	0.95	17
floodplain bed width, b_f (m)	2.25	2.25	2.25	4.1	1.05	63,21
Bankfull depth, h (m)	0.15	0.15	0.15	0.15	0.1	6.0
Width ratio, (B/b_c)	4.2	2.6	4.2	6.67	3.21	4.94
Main channel side slope, s_c	1.0	1.0	1.0	1.0	0.0	1.5
Floodplain side slope, s_f	1.0	1.0	1.0	0.0	0.0	4.0
Floodplain type	Symmetric	Asymmetric	Symmetric	Symmetric	Asymmetric	Asymmetric
Floodplain roughness	Smooth	Smooth	Rough	Smooth	Smooth	Rough
Bed Slope, S_0	0.001027	0.001027	0.001027	0.001027	0.00104	0.000185
Manning's n for main channel, n_c	0.01	0.01	0.01	0.01	0.01	0.03
Manning's n for floodplain, n_f	0.01	0.01	0.01-0.03	0.01	0.0105	0.028, 0.04
Relative depth, Dr	0.157-0.30	0.24, 0.3	0.15-0.3	0.20, 0.25	0.42, 0.46	0.07, 0.232
Reynolds number, Re (10^5)	1.73-2.91	3.18-3.63	1.56-2.07	2.20-2.81	3.06, 3.54	97, 115
Number of experiments	4	2	4	2	2	2

5. Results and Discussion

The UK-FCF experimental data (Series 02, 06 and 07) were used to perform parameter estimation. As seen in Table 1, the cross-section of FCF Series 02 is a symmetric trapezoidal compound channel with smooth concrete (*n* =0.01). The FCF-07 section has exactly the same dimensions as Series 02, but its floodplains are roughened by un-submerged wooden rods. FCF-06 section is similar to Series 02, except that it is an asymmetric compound channel with one floodplain.

For GA implementation, a code was written in Visual Basic Application for Microsoft Excel. Using 10 data sets of lateral velocity distributions, the following equations were obtained for the main channel and the floodplain by GA, respectively:

$$\frac{u_i}{u_{iMan}} = Dr^{0.2048}COH^{b_1} \qquad (7)$$

$$\frac{u_i}{u_{iMan}} = Dr^{0.2048}COH^{b_2} \qquad (8)$$

where the exponents b_1 and b_2 have the following relationships with corresponding determination coefficients of R^2=0.95 and 0.94, respectively:

$$b_1 = -0.832Dr^{2.898}\left(\frac{h_f}{h}\right)^{-2.9}\left(\frac{n_f}{n_c}\right)^{-1.571}\left(\frac{b_f}{B/2}\right)^{-0.369} \qquad (9)$$

$$b_2 = -2.139Dr^{0.667}\left(\frac{h_f}{h}\right)^{-0.283}\left(\frac{n_f}{n_c}\right)^{0.138}\left(\frac{b_f}{B/2}\right)^{-0.776} \qquad (10)$$

For validation of the proposed equations (7-10), they were applied to three different cases, not used in the calibration process, including the FCF Series 01, data by Guan (2003) and field data of the River Severn (Knight et al. 1989). FCF Series 01 has two rectangular floodplains with each being 4.1m wide. For Guan's flume data, the Manning roughness coefficients for the main channel and the floodplain are considered to be 0.01 and 0.0105, respectively (Guan, 2003). The River Severn has a section with two inclined berms being 63m and 21m wide, respectively. The Manning's roughness of the main channel is 0.03, and for left and right floodplains are 0.028 and 0.04, respectively (Knight et al. 1989).

The predicted results based on Eqs. (7)-(10) for the three compound channels are illustrated in Figs. 3-5, which show good agreement with the observed data in both flume and river compound channels. Despite different types of channel geometry, roughness and hydraulic characteristics, the proposed equations (7)-(10) can be used to predict velocity distribution well in the main channel and floodplains. However, there is some deficiency of the predicted results in the region around the interface between the main channel and its floodplains (shear layer regions). This velocity deficiency may be due to the simple equations adopted and applied with the same parameters in the entire section of either main channel or floodplain. It should be noted that flow is very complex in the shear layer near the interface

due to strong momentum exchange between the main channel and its floodplains, so it is always challenging to predict the velocity distribution very well in this small region, like any other methods.
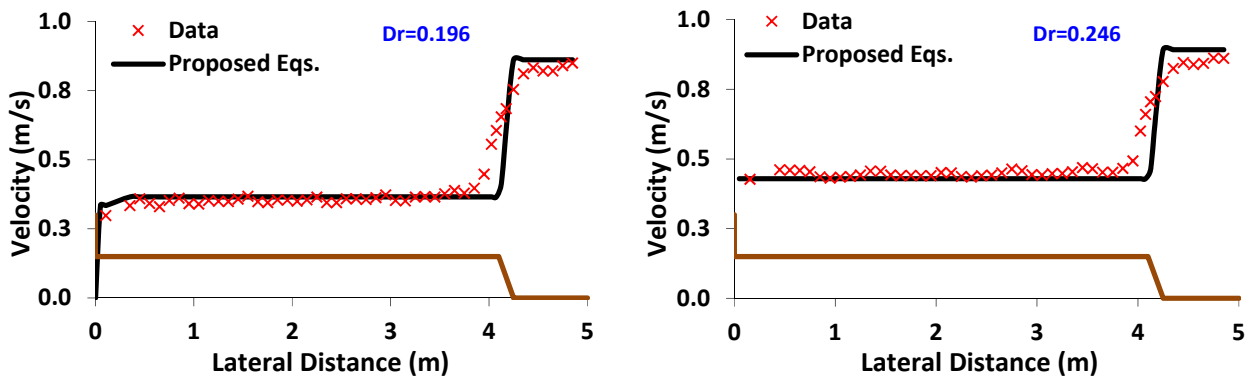

Fig. 3. Comparison of predicted and observed lateral velocity distributions in FCF-01 section (h=0.15 m)
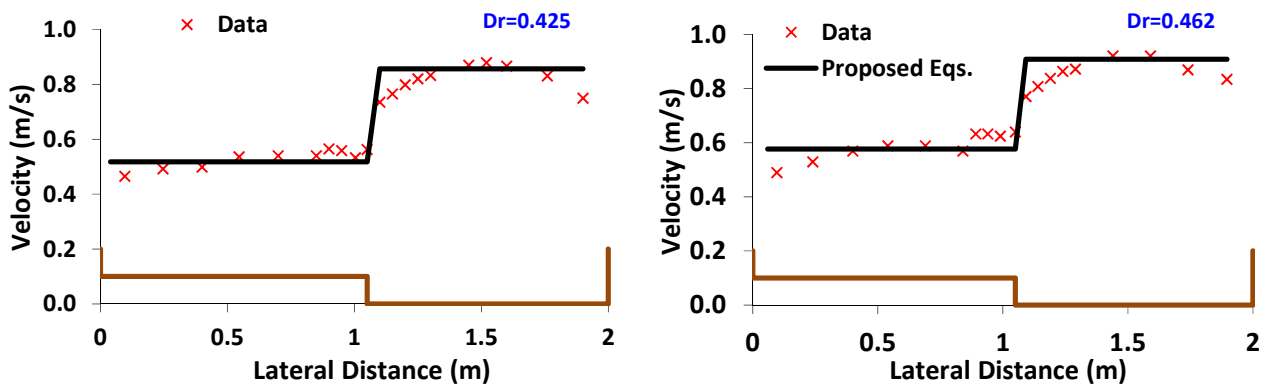

Fig. 4. Comparison of predicted and observed lateral velocity distributions in Guan (2003) section (h=0.10 m)
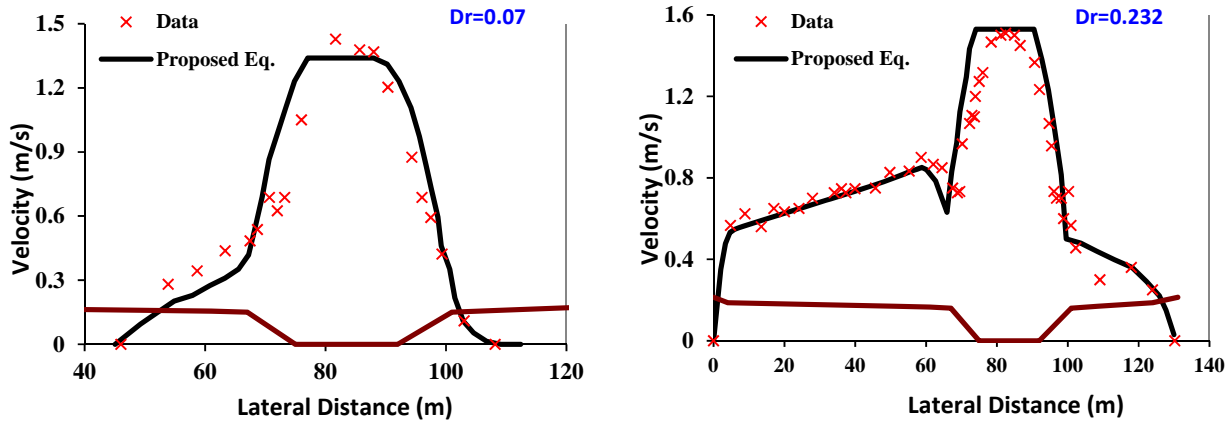
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Fig. 5. Comparison of predicted and observed lateral velocity distributions in River Severn (h=6.0 m)

To evaluate the accuracy of the proposed equations in calibration and validation phases, two common statistical measure parameters, coefficient of determination (R^2) and root mean squared error (RMSE), *are used in the study as follows:*

$$R^2 = \left(\frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \right)^2 \qquad (11)$$

$$RMSE = \sqrt{\frac{\sum (X-Y)^2}{N}} \qquad (12)$$

where $x = (X - \overline{X})$, $y = (Y - \overline{Y})$, $\overline{X}$ is the mean of X, and $\overline{Y}$ is the mean of Y. The results of computation show good accuracy for the proposed equations, where R^2=0.93 and RMSE=0.063 for calibration set and R^2=0.92 and RMSE=0.112 for validation set. The high value of R^2 demonstrates prediction reliability of the simple equation. Therefore, the proposed equations (7)-(10) may be used as a fast and accurate approach for prediction of lateral velocity distribution and so as the flow discharge in flooded rivers.

By lateral integration of velocity distributions, one can calculate sub-area and total flow discharges of compound channels to obtain stage-discharge rating curves. The predicted stage-discharge results are

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presented in Fig. 6 for both the flumes (FCF Series 01, 02, 06, 07 and Guan (2003)) and natural compound sections (River Severn), where the results obtained from the traditional vertical divided channel method (VDCM) have also been included for comparison. Fig. 6 shows that the predicted results from the proposed equations agree very well with the observed flow discharges, especially for the compound flumes, whereas the VDCM method does not. In the case of compound flume channels, the mean and maximum errors of proposed equations are 2.4% and 16.4%, respectively, whilst these statistical measures are 13.6% and 45.7% for VDCM. Fig. 6 also shows that the discharge of river Severn is over-predicted to some extent for high flow despite good agreement of velocity distribution. This indicates increasing uncertainty in the measurement in high flow conditions. Nevertheless, the results in Fig. 6 demonstrate that some deficiency of velocity in the shear layer does not have much impact on the prediction of discharge.
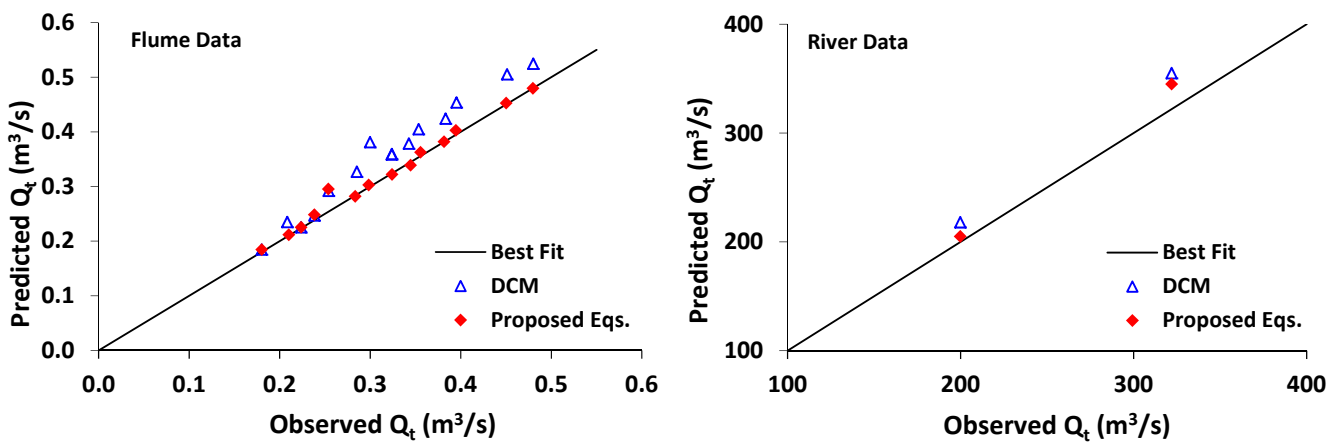

Fig. 6. Comparison of predicted (from proposed equations and DCM) and observed total flow discharges Q_t for flume (FCF Series 01 and Guan (2003)) and river compound channel (River Severn)

6. Conclusion

A new simple model (3) for computation of lateral depth-averaged velocity distribution in compound channels has been proposed based on two commonly used dimensionless parameters, *Dr* and *COH*. The

proposed model is expressed by two different equations (7) and (8) for main channel and flood plain respectively. The optimal parameters in formulas (9) and (10) have been obtained by genetic algorithm (GA) using various experimental data with different geometric and hydraulic conditions. The proposed equations have been validated and have a high determination coefficient (0.93 and 0.92, for calibration and validation, respectively) and low root mean squared error (0.063 and 0.112, for calibration and validation, respectively). The prediction of depth averaged velocity distributions based on the proposed equations (7)-(10) have shown good agreement with both flume data and field data of river despite some deficiency in a small region around the interface where strong momentum exchange exists. Due to their simplicity and reliability, the proposed equations can be used as a fast and accurate approach for predicting lateral velocity distributions as well as the total flow discharges in flooded rivers. Finally, the proposed optimized model has some limitations for compound channels with rectangular cross sections. In these sections, all parameters in Eqs (3) and (5) are constant for main channel and floodplains. This limitation may have some deficiency for velocity prediction in mixing or shear layer between main channel and floodplains (as seen in Fig. 4 for Guan's data). However, river compound channels are usually non-rectangle in shape, and hence this limitation is not significant in practical applications.

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