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Flow Variables Prediction Using Experimental, Computational Fluid Dynamic and Artificial Neural Network Models in a Sharp Bend

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ABSTRACT

Bend existence causes changes in the flow pattern, velocity and the water surface profile. The ability to simulate three-dimensional flow pattern is an important and significant issues in curved channel. In the present study, using three-dimensional model of computational fluid dynamics (CFD) and artificial neural network (ANN) model of multi-Layer perceptron (MLP), two velocities and pressure variables on the channel bed with 90º sharp bend is predicted and compared. Also extensive experimental work has been conducted to measure the flow variables in this bend. Experimental results are used to train and test the neural network model accordingly. Comparison of the numerical with experimental results show that CFD model with average Root Mean Square Error (RMSE), 0.02 and 0.13 and ANN model with R^2 (determination coefficient) value, 0.984 and 0.99 to predict velocity and pressure respectively, has reasonable accuracy. Also, velocity pattern and flow pressure with both numerical (CFD and ANN) models at any point of the field channel is predictable. Comparison of the CFD and ANN models show that the ANN model with the average value of Mean Absolute Error (MAE), 0.048 to CFD model with the average MAE, 0.06 in prediction of velocity and pressure has more accuracy. The present neural network with less time and cost in designing and implementation of curved channels than other expensive and time consuming experimental and computational models can be used.

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1. INTRODUCTION

In the path of rivers and artificial channels can be seen that there are several curves which caused considerable difficulties in understanding the flow pattern in this path. Therefore, the characteristics of the flow in this region are great importance of hydraulic researchers. The numerical and experimental studies have been done a lot in this area. Blanckaert and Graf [1] carried out wide experimental investigations on a 120° sharp bend, and paid the pattern of turbulent flow in the bend. The results showed that the lack of shear stresses coordination in the cross-section led to the formation of the secondary rotating cell near the outer bend of 60° cross section. Lu et al. [2] did numerical study in a 180° curved channel. The researchers found that in the channel width of the curved part, flow direction tilted initially at 0° to 90° toward the inner wall and then at 90° to 180° toward the outer wall of channel. Bodnar and Prihoda [3] using the finite volumes method paid numerical study of the free surface flow in 90° sharp bend and focused on non-linear gradient of water surface. Zhang and Shen [4] investigated water level changes, longitudinal and transverse velocity profiles and flow separation phenomena in curved channels by a three-dimensional numerical model. Naji et al. [5] did numerical and experimental simulation of flow patterns in 90° bend. They investigated the changes of the flow velocities component, streamlines, bed shear velocity and the secondary flows. Their results showed that the main cause of changes in velocities component are secondary flows. Gholami et al. [6] examined the flow pattern in the 90º sharp bend according to extensive experimental research and computational fluid dynamics model. In addition, velocity distribution, the

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shear stress distribution, streamlines, velocity contours and secondary flow formation was studied as well. The result is considered as the maximum velocity position and displacement. They stated that the maximum velocity in sharp bends to the end sections of the bend remains in the vicinity of the inner wall. There are many other numerical studies about channels [7-11].

In recent decades, artificial intelligence methods in addition to reduce the computation time, are able to predict the flow parameters in all conditions, especially in places where experimental data are not available. Therefore, in recent years the useing of these methods has a special place among water engineers [12-21]. A MLP model is a type of artificial neural network used for predicting variables. Sahu et al. [22], used artificial neural networks to study and predict the velocity profiles in open channel meanders. The correlation coefficient between results showed the efficiency and accuracy of the neural network model to predict the velocity. Bonakdari et al. [23] predicted the velocity field values in a mild bend using ANN and the Genetic Algorithm. They used three-dimensional numerical modeling to verify the results where no experimental results were available. Their results indicated that there is an acceptable level of consistency between the results of the numerical and ANN models. Baghalian et al. [24] took a sediment tool into account and studied the flow in a 90° mild bend. According to their results, the numerical and ANN models were more consistent with the experimental values compared with the analytical solution. Gholami et al. [25] predicted two velocity and water surface variables in 90º sharp bend using both CFD and MLP models. They decared that the ANN model perform more accurate than CFD model.

In this study, the two variables velocity and channel bed pressure is investigated at 90° sharp bend by using two different numerical models (CFD and ANN) which is rarely addressed in previous studies. First, a computational fluid dynamics model is used to investigate the three-dimensional flow pattern in sharp bends. In the end, two artificial neural network models is trained to based on available experimental data to predict the flow velocity and pressure. The performance of these models to predict the velocity and channel bed pressure are assessed by using three statistical parameters: R^2, *RMSE*, and *MAE*.

2. GOVERNING EQUATIONS

Governing equations are the equations of continuity and momentum equations in the incompressible turbulent flow with viscosity and constant density as an average of the time can be expressed as follows:

$$\frac{\partial \rho}{\partial t} + div\,(\rho U) = 0 \tag{1}$$

$$\frac{\partial \bar{u}_i}{\partial t} + \bar{u}_j \frac{\partial (\bar{u}_i)}{\partial x_j} = -\frac{1}{\rho}\frac{\partial \bar{P}}{\partial x_i} + g_{x_i} + \frac{\partial}{\partial x_j}\left[\nu \frac{\partial \bar{u}_i}{\partial x_j} - \bar{u}_i \bar{u}_j\right] \tag{2}$$

$\bar{u}_{i(j)}$ = The velocity component in the direction *i* (*j*), *P*= total pressure, ρ = Density of the fluid, ν= molecular viscosity, g_{x_i} = gravitational acceleration in the direction x_j and $\bar{u}_i \bar{u}_j$ = the Reynolds stresses that apply turbulence effect on the fluid.

3.NUMERICAL AND EXPERIMENTAL MODELS

The desired solution field is consistent with the available experimental model, the channel details are a 90° curved channel with two straight channels in the upstream and downstream. The length of upstream 3.6m and downstream channel 2m is considered and the dimensions of the rectangular channel is 30cm×40.3cm (height and width of the channel); the central angle of bend is 90° and central radius is 60.45 cm (R_c= 60.45cm), according to the channel width (b = 40.3cm) bend is sharp (R_c/b= 1.5<3). Bed and walls of the channel are fix and made of Plexiglas, and manning coefficient is n=0.008, so the cross section is hydraulically smooth. To measure the longitudinal velocity, the PROPLER one-dimensional velocity meter was used. The flow height was measured with a micrometer. The micrometre measured the depth with 0.1 mm precision and the velocity with 2 cm/s precision [6, 26]. Flow hydraulic characteristics are shown in Table 1. Considering the Froude number= 0.34 and Reynolds number=44705, flow regime is subcritical and turbulent. Figure 1 is shown a view of the experimental flume.

To construct the numerical model, as shown in Figure 2 the geometry of the flow field created in the software Gambit then to adjust the grid of flow field near the channel bed, walls, inside the bend and also at the interface of the two phases finer gridding and in other areas larger gridding is considered. In general, network with 73,346 nodes is generated. In the present numerical model, for closure equations, $k-\varepsilon\,(RNG)$ turbulence model is used.

TABLE 1. Hydraulic characteristic of the tests

Flow Discharge (lit/s)	25.3
Velocity (m/s)	0.418
Flow depth (cm)	15
Froude number	0.34
Reynolds number	44705

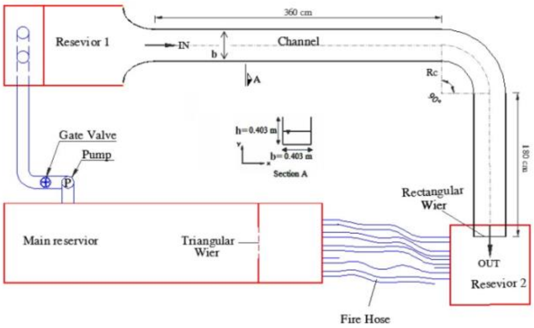


Figure 1. The geometry of the experimental model

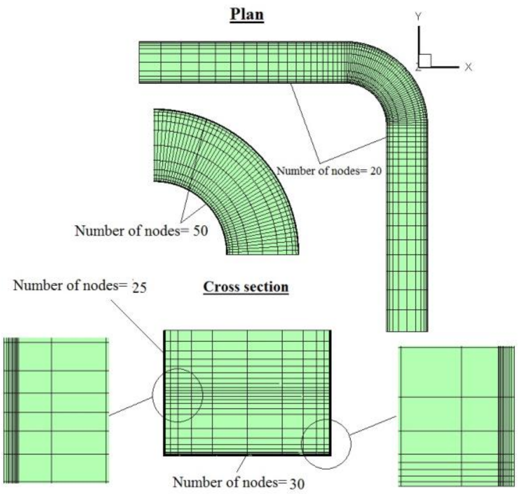


Figure 2. Gridding of 90° bend in plan and cross-section

Boundary condition for the flow entrance is *Velocity Inlet* that for the water and air phase is considered separately. Free surface boundary condition *Pressure Inlet* in the case of two-phase flow, the outlet boundary condition *Pressure Outlet* in the *open channel* state and *free surface level*, and boundary condition of the bed and the walls *Wall* have been considered.

4. ARTIFICIAL NEURAL NETWORK (ANN) MODEL

Implementation of the amazing features of the brain in an artificial system is always tempting and desirable. Generally, an artificial neural network composed of interconnected nodes called neurons, that in three basics layers input, hidden, and output are arranged. Neurons in each layer are connected to the neurons of the next layer by weights. In this study, the multi-layer perceptron neural network (MLP-NN) is used. The flexible structure of MLP in simulation of nonlinear problems with their high efficiency causes the widespread use of this model in practical conditions [13, 27]. The structure of a multi-layer perceptron consists of one input layer and one or more hidden layers and one output layer is shown in Figure 3.

The MATLAB R2011b software is utilized to prepare a proper neural network model. The input layer introduces the input variables to the model with neurons and transmits them to the hidden layer. The hidden layer gatters the input layer neurons by using a weighted summation and so transmits them to a non-linear future by activation functions. MLP models often use sigmoid activation functions [28, 29]. Any function that has a proportional relation between the input and output variables is a sigmoid function. In the present study, the hyperbolic tangent activation function is used for the hidden layer (Equation (1)) [30]:

$$tanh(x) = \frac{2}{1+e^{-2x}} - 1 \tag{3}$$

The output layer of the MLP performs like a linear regressor. Therefore, a weighted summation of the hidden layer neurons is done in this layer to asseses the final model results. The number of input and output layer neurons is equal to the number of input and output model variables, respectively. Two separate neural network model are trained for predicting the velocity and the other one to predict the channel bed pressure. At the ANN model for velocity prediction, 3, 40, and 1 neuron respectively in the input layer, hidden layer, and output layer are used. Where the inputs are point coordinates in three dimensions (x, y, z) and the output is velocity corresponding to these points. At the network of the pressure prediction, 2, 30, and 1 neuron respectively in the input layer, hidden layer, and output layer is used. In this model, points coordinates on the channel bed are input and output is the pressure of points. There are no specific rules for determining the number of neurons in the hidden layer. If the number of neurons is very low, it reduces the analysis capability and the numerical accuracy of prediction. However, if the number of hidden layer neurons is excessively high, the model will undergo overtraining and memorize rather than analyse the data. Therefore, using the trial and error method [23, 25, 31] and considering the different number of neurons in the hidden layer, various models are tested and the model that provided the best results as final neural network model is selected. The hidden and output layers need weighted summations. Determination of weight coefficient in MLP model is named training. In the present paper, Levenberg-Marquardt (LM) method is used for training process [32]. The LM method uses backpropagation algorithm for model weight determination. Criteria “stop” training in the present study is considered 100 epoch which occurs when the model converges completely [19, 31]. An epoch is considered an iteration. The number of epochs (iterations) was selected relative to each model until network reached an acceptable error level between the data obtained with the ANN model and the experimental data. The model should converge for each number of epochs. In the present study, given that the MLP models converged at 100 epochs, the number of epochs considered was 100.

- At the ANN model for velocity prediction: In this study, a total of 320 experimental data were used to train the network, of which 225 and 95 data have been used to train and test the network, respectively.
- At the ANN model for bed pressure prediction: 104 experimental data (75 data for training and 29 data for testing the network) is used. Cross sections, points located on the each cross section, and the distance from the channel bed (z) are shown in Figure 4. For the velocity network, this points in three distance from the bed of the channel (z = 3, 6, and 9 cm) and for the pressure network points at the bed of the channel network (Z = 0) are used.

5. RESULTS AND DISCUSSION

5. 1. Statistical Indices In the present study, to better compare experimental data and the results of numerical models, some error criterion is used. "Root Mean Square Error" is briefly called *RMSE* indicates the difference between the estimated and measured data is obtained from Equation (4), the other way "determination coefficient" or R^2 according to Equation (5) and "Mean Absolute Error" is called *MAE* for short, is obtained from Equation (6):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - t_i)^2}{N}} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(O_i - t_i)^2}{\sum_{i=1}^{N}\left(O_i - \overline{O}_i\right)^2} \tag{5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|O_i - t_i| \tag{6}$$

In these equations, N is the number of measurement points, t_i experimental measured data and O_i predicted by the model and $\overline{O}$ the mean of the model values. The lower *RMSE* and *MAE* value and the greater value of R^2, indicating the high accuracy of the model was estimated and predicted more consistent with experimental data. The *RMSE* and *MAE* values show the difference between experimental and numerical values by the same scale and unit and as the values are closer to zero, the model accuracy will be high.

5. 2. Model Performance Evaluation Figures 5 and 6 show the correlation analysis between the velocity values and the bed pressure values predicted by the ANN model and the experimental data in train and test states, respectively. The *RMSE* and R^2 is shown above each figure. At the Figures 5 and 6, it can be seen that all data on both sides of the line fitted with a 45º angle have been largely symmetrical. Also, shown in Figure 5, in train state, R^2 equal to 0.9834 and the network test state, the R^2 value is equal to 0.984. At the bed pressure prediction network, the R^2values at the train and test states are 0.9883 and 0.99, respectively. Due to the proximity of the R^2 value in the train and test states, can be concluded that both obtained ANN models are not been over train. In this figure, linear fitted line equation with $y=C_1x+C_2$ is used. The value of C_1 and C_2 is closer to 1 and the value of C_2 is closer to 0, the proposed model is more accurate. The given values of C_1 in Figure 5 at the train and test state are 1.0121 and 1.006, respectively. Also, the amount of C_2 in this relationship are 0.0018 and 0.0113 that can contribute to the accuracy of ANN model to predict the velocity in train and test states, respectively. In Figure 6, the values of C_1, at the train and test states are 1.0121 and 1.006, respectively, and the value of C_2 in this relationship are 0.0018 and 0.0113, respectively, which indicate the accuracy of the ANN model to predict the pressure on the bed of the channel in the train and test states. Given these values, we find that both ANN models are well-trained and their performance in predicting the velocity and the channel bed pressure are satisfactory.

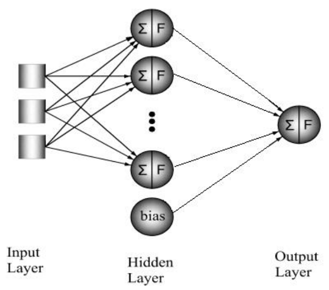


Figure 3. Multi- layer perceptron network general diagram

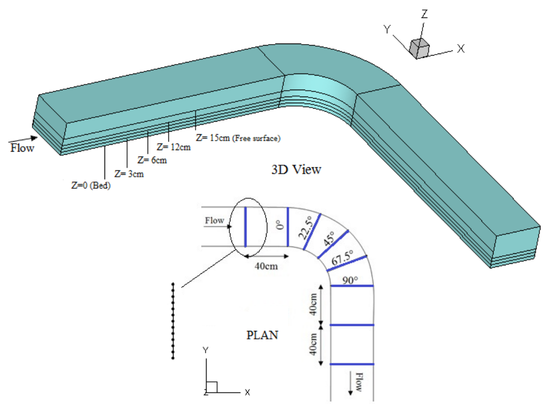


Figure 4. Various used points in each cross section and in different Zs in order to train ANN models

5. 3. Models Comparison In Figure 7, the longitudinal velocity distribution simulated by CFD and ANN models have been compared with experimental data in different cross sections in the Z = 3cm level (near the channel bed). In Table 2, the *RMSE* and *MAE* values have been collected for the velocity transverse profiles between the results obtained from the CFD and ANN models with experimental data in different cross sections. According to figures, the CFD results with experimental results coincide with the *RMSE* average value of 0.0205 and *MAE*, 0.018. The *RMSE* value of 0.008 and *MAE* of 0.006 between ANN model results with experimental data shows high accuracy of ANN model in predicting velocity. In Figure 8, the transverse pressure profiles predicted by CFD and ANN models are compared with experimental data on the channel bed in 8 cross section. In Table 2, the amount of error (*RMSE* and *MAE*) is given between the predicted results of pressure distribution in different cross sections (Figure 8). Be careful of these values, can be seen that the CFD model with *RMSE*, 0.13 and *MAE*, 0.11 cm in accordance with experimental results is acceptable.

The CFD model with the *RMSE* average value of 0.12 and *MAE*, 0.11 acts well in prediction of pressure variable. With the arrival to the bend, due to the centrifugal force creation, transverse slope of the water surface decreases at the inner wall of the channel and increases at the outer wall.

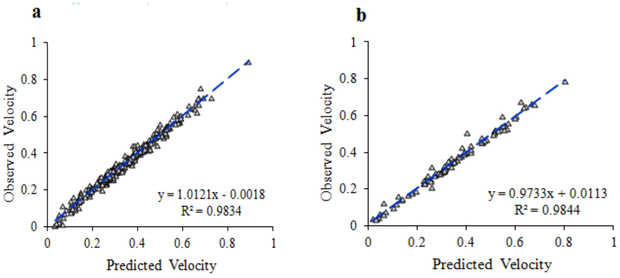


Figure 5. Comparison of velocity values predicted by the CFD model and experimental model in: a- Train and b- Test states

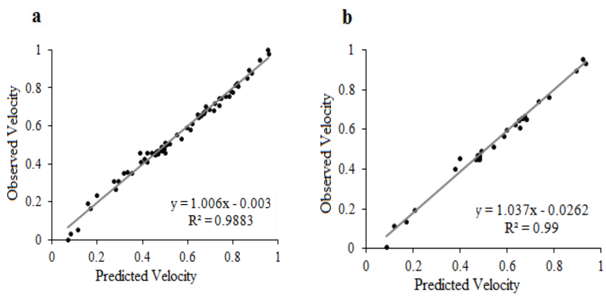


Figure 6. Comparison of pressure values predicted by the ANN model and experimental model in: a- Train and b- Test states

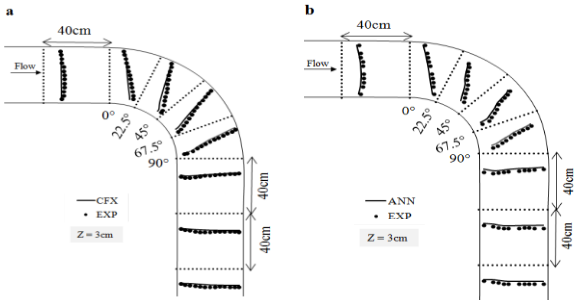


Figure 7. Comparison of transverse profiles of longitudinal velocity at: a- CFD model with experimental data and b- ANN model with experimental data

The pressure value is equal to height of water surface multiple in specific gravity ($p = \gamma \times h$), where p, the pressure, h, water surface height and γ specific gravity of the water is equal 9810 (N / m^2). Therefore, the pressure changes are like water surface changes pattern in channel bed. So, in the inner cross sections, the maximum pressure occures in the outer wall and the minimum pressure occures in the inner wall of the channel. This process creates transverse pressure gradient within the cross section of the channel. As in the channel bed, pressure gradient overcomes to the centrifugal force and at the water surface, the centrifugal force to the pressure gradient, and so the rotational cell is created in channel cross section. This rotational flow is moved to the inner wall at the channel bed and to the outer wall at the water surface. This rotational cell called secondary flow phenomena that are typical subjects of the curved channels. As previously mentioned, a neural network has been trained and ensured their performance. In this section, we will study the velocity distribution by ANN model in the points which no experimental data are available and then to compare these values with the values obtained by the CFD simulations. In this study, the experimental data obtained only in 8 sections but neural network can study the velocity and water depths values in other sections. In Figures 9, the depth averaged velocity distribution are predicted in the different cross sections by the ANN and CFD model and compared by each other.

In Table 3, the *RMSE* and *MAE* amounts are given between the results of ANN and CFD model to predict pressure distribution in different cross sections (Figure 9). As can be seen, both models (ANN and CFD), are well able to predict the average velocity at different cross sections, also there is acceptable match between the results of both models with the *RMSE*, 0.08 and *MAE*, 0.066. In this figure carefully and as described, the maximum velocity occurs at the channel inner wall. Forward along the bend, due to the power of the secondary flow, maximum velocity goes to channel axis, and finally moves to the outer wall in the section located after the bend.

TABLE 2. Comparing velocity and pressure distribution in the CFD and ANN model with the experimental model at Z = 3cm from the channel bed at different cross sections

	Velocity Prediction				Pressure Prediction			
	CFD model		ANN model		CFD model		ANN model	
Cross Section	*RMSE*	*MAE*	*RMSE*	*MAE*	*RMSE*	*MAE*	*RMSE*	*MAE*
40 cm before	0.026	0.023	0.008	0.006	0.0048	0.0047	0.0047	0.0045
0°	0.029	0.024	0.0075	0.006	0.12	0.09	0.10	0.09
22.5°	0.03	0.027	0.006	0.005	0.096	0.087	0.11	0.09
45°	0.027	0.025	0.005	0.004	0.12	0.096	0.12	0.094
67.5°	0.022	0.019	0.0055	0.003	0.22	0.2	0.24	0.20
90°	0.01	0.01	0.0123	0.008	0.15	0.105	0.14	0.095
40 cm after	0.009	0.008	0.008	0.0055	0.13	0.12	0.127	0.1
80 cm after	0.0115	0.009	0.0102	0.008	0.165	0.164	0.176	0.17
Averaged Values	0.0205	0.018	0.008	0.006	0.13	0.10	0.127	0.09

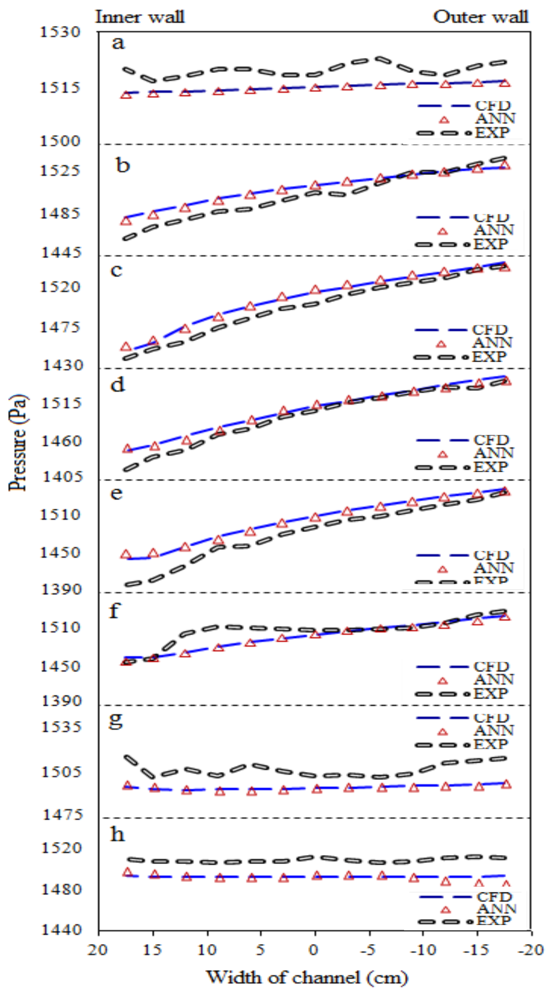
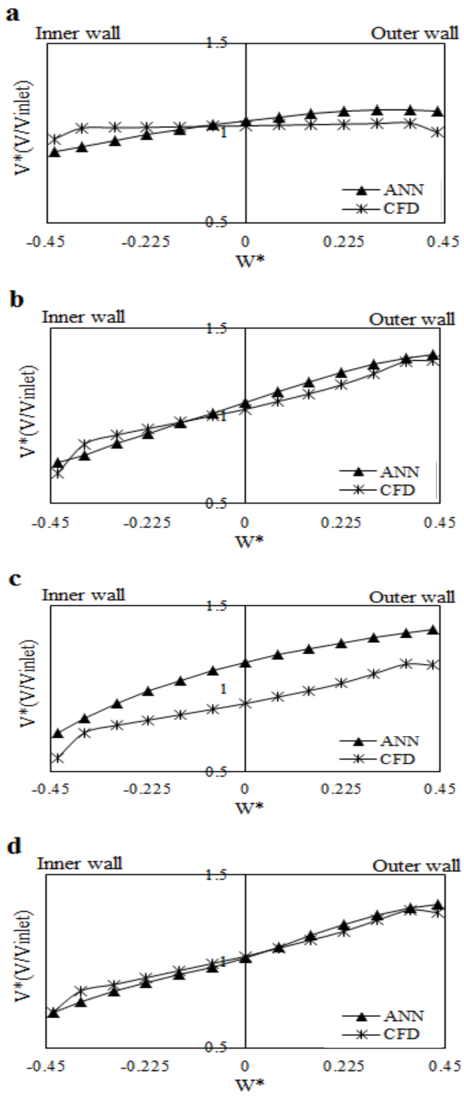


Figure 8. Comparing pressure distribution in the CFD and ANN model with the experimenyal model at: (a) 40 cm before the bend, (b) 0°, (c) 22.5°, (d) 45°, (e) 67.5°, (f) 90°, (g) 40 cm and, (h) 80 cm after the bend cross sections



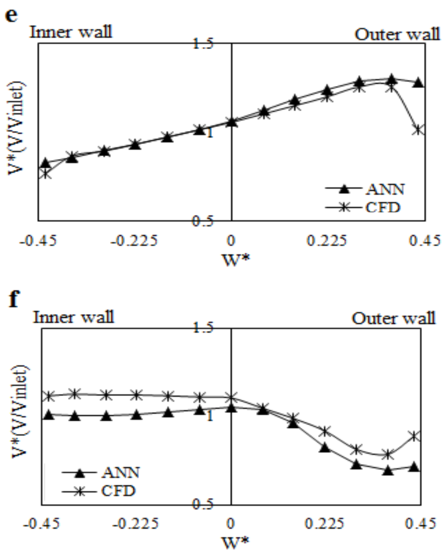


Figure 9. Comparing depth averaged velocity distribution in the CFD and ANN model at: (a) 30 cm before the bend, (b) 20°, (c) 30°, (d) 50°, (e) 70°, and (f) 30 cm after the bend cross sections

TABLE 3. Comparing pressure distribution in the CFD and ANN model at channel bed at different cross sections

Cross Section	*RMSE* (cm)	*MAE* (cm)
30 cm before the bend	0.068	0.06
20°	0.048	0.043
30°	0.207	0.2
40°	0.05	0.043
50°	0.031	0.026
60°	0.034	0.028
70°	0.08	0.04
30 cm after the bend	0.096	0.09
Averaged Values	0.08	0.066

Another point to note is that in the present sharp bend, the position of the maximum velocity is often in the inner portion of bend because of longitudinal flow power and its dominance on the secondary flow in these bends.

6. CONCLUSION

In the present study, experimental model, finite volumes numerical model and neural network model are used to predict the velocity and channel bed pressure at a 90° sharp bend. For this purpose, at first the numerical computational fluid dynamics model is used to simulate the bend's flow pattern. The two multi-layer perceptron neural network (MLP-NN) models have been trained to predict the velocity and pressure of channel bed. Acceptable compliance of the both CFD and ANN numerical models results with experimental model represents the high accuracy of numerical models in prediction of two velocity and flow pressure variables in 90º sharp bend. Both models predict the velocity and pressure pattern on the channel bed as well. In sharp bends, the maximum velocity is happened in the inner wall and moves to outer wall of channel in the sections located after the bend which is predicted well by two CFD and ANN models. However, in comparison of two models, it can be said that the ANN model with less error value than the CFD model perform more accurate. Both models can also predict the flow variables values in other parts and cross sections of channel which there is no experimental data, accordingly. The ANN model with time-consuming and less expensive than the CFD model is able to predict the flow velocity and pressure at each point of the channel.

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Flow Variables Prediction Using Experimental, Computational Fluid Dynamic and Artificial Neural Network Models in a Sharp Bend

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چکیده

وجود قوس موجب تغییر در الگوی جریان، پروفیل سرعت و سطح آب می‌گردد. توانایی شبیه سازی الگوی جریان سه بعدی از موضوعات مهم و قابل توجه در کانال های خمیده می باشد. در تحقیق حاضر، با استفاده از مدل سه بعدی دینامیک سیالات محاسباتی و مدل شبکه عصبی چند لایه ی پرسپترون، دو متغییر سرعت و فشار وارد بر کف کانال قوس تند ۹۰ درجه پیش بینی و مقایسه می شود. همچنین تحقیقات آزمایشگاهی گسترده ای در اندازه گیری متغییرهای جریان در این قوس انجام شده است. از نتایج آزمایشگاهی موجود برای آموزش و تست مدل شبکه عصبی استفاده می شود. مقایسه ی نتایج حاصل از مدلهای عددی با نتایج آزمایشگاهی نشان می دهد که مدل دینامیک سیالات محاسباتی با مقدار متوسط مجذور مربعات خطا برابر ۰/۰۲ و ۰/۱۳ و مدل شبکه عصبی با مقدار ضریب تشخیص ۰/۹۸٤ و ۰/۹۹ برای پیش‌بینی به‌ترتیب سرعت و فشار جریان دقت قابل قبولی دارند. همچنین الگوی سرعت و فشار جریان به کمک هر دو مدل عددی (دینامیک سیالات محاسباتی و شبکه عصبی ممصنوعی) در هر نقطه از میدان حل قابل پیش‌بینی می‌باشد. مقایسه ی این دو مدل با هم نشان می دهد که مدل شبکه عصبی با مقدار متوسط خطای مطلق ۰/۰٤۸ نسبت به مدل دینامیک سیالات با متوسط خطای مطلق ۰/۰٦ در پیش‌بینی سرعت و فشار دقت بیشتری دارد. می توان از مدل شبکه عصبی حاضر با صرف وقت و هزینه ی کمتر در طراحی و اجرای کانال های خمیده بجای دیگر مدلهای گران و وقت گیر آزمایشگاهی و محاسباتی استفاده کرد.

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