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Prediction Coefficient of Pressure and Wall Friction for Turbulent Flow over a Backward Facing Step

Zaid Al Kahfi Ramadhan[a], Mohamad Yamin [b*]
[a]Lab Center of Automotive Research Universitas Gunadarma,
[b] Jurusan Teknik Mesin Universitas Gunadarma,
Jl. Margonda Raya No.100, Kota Depok, Provinsi Jawa Barat, Kode Pos 16424
*e-mail: mohay@staff.gunadarma.ac.id

Abstract

Backward Facing Step (BFS) has been widely recognized for its application to turbulence fields in deep flow. The flow separation occurs due to a sudden change in geometry. To know the phenomenon of flow in BFS, it can be conducted with a numerical approach. In some cases, numerical studies have a weakness in the computational time aspect. This study focuses on the prediction of Cp and Cf on BFS flow using Machine Learning. It begins with a meshing sensitivity approach with the number of elements as much as 22188 cels in a numerical simulation with a step height of 12.7 mm. This numerical study was carried out using Reynolds number in the turbulent region of Re 36000. The turbulent k-omega shear stress transport model was used to perform numerical simulations in the open-source software package OpenFOAM®. Simulation data in the form of speed and pressure at each node that represents the form of turbulence was used as a dataset in Machine Learning. Three Machine Learning models, namely Multi-Layer Perceptron, RandomForrest, and Multiple Linear Regression were used to predict Cp and Cf. The effectiveness of each of these models is -101.5% for Multi-Layer Perceptron, 96% for RandomForrest, and 99% for Multiple Linear Regression. With the best effectiveness value, the Machine Learning Multiple Linear Regression model is used to get the predicted Cp and Cf values from variations in step height of 9.525 mm, 6.35 mm, and 3.175 mm. With these results, it shows that the Machine Learning model can be used to predict the BFS turbulence flow obtained from the results of the OpenFoam® numerical approach.

Keywords: *Backward Facing Step, Machine Learning, OpenFoam, Cp Prediction*

1. Introduction

Computational fluid dynamics (CFD) is a numerical method for analyzing the structure and data of a fluid flow [1]. The use of the CFD method is a faster and cheaper alternative in research compared to conducting experimental studies. The backward-facing step (BFS) is a geometric model that can be analyzed using a CFD numerical approach. Backward Facing Step (BFS) is widely known for its application in the study of turbulence. BFS is one of the representation models for the separation of a stream. The flow separation in BFS is caused by a sudden change in geometry [2]. Various applications for BFS flow can be found in everyday life, such as airfoils, spoiler flows, flow separators behind vehicles, as well as flows around ships or buildings.

[3] investigated the flow of BFS in three flow areas, namely laminar, transitional, and turbulent with a Reynolds number of 70-8000. These three areas are studied theoretically, experimentally, and computationally. It is concluded that the difference in flow characteristics occurs because of the difference in the separation height (step). [4] performed a numerical simulation of BFS in OpenFoam® using the k-ω SST turbulence model at Reynolds number 5000. The result was that the numerical simulation data had a

positive trend and was well compared to the experimental data verified by [5]. At other times, [6] performed a numerical simulation of the BFS in OpenFoam® using the Standard k-epsilon (k-ε) turbulence model in the Reynolds Number region >6600 based on the geometry [3] and the result is that the higher the Reynolds number, the Cp value will decrease, while the Cf value will increase.

The use of machine learning has helped humans in everyday life. Today, machine learning can be found in all fields, including aerodynamics. Machine learning is used to reconstruct information on the flow model. [7] investigated the ability of a machine learning multilayer feed-forward neural network model to reconstruct data from large eddy simulation (LES) simulations. [8] conducted a detailed investigation of the ability of the neural network to reconstruct functions in the Spalart Allmaras turbulence model and demonstrated that it is indeed possible to replace the analytical representation of machine learning with the solver built into the CFD. The purpose of the study in this paper focuses on the prediction of Cp and Cf from the results of a 2-dimensional BFS numerical simulation using OpenFoam® using machine learning methods.

2. METHODS

2.1 Computing Method

Geometry is created using OpenFoam® along the x,y, and z axes. For two-dimensional conditions, the fixed unit width is assigned to the model. The geometry and meshing are shown in Figure 1 and Figure 2. The expansion ratio (H/h) is 1.12 (H=114.3 mm & h=101.68 mm) with a step height of 12.62 mm.

Geometry is divided into 6 blocks, by following the names of the inlet, outlet, upper-wall, lower-wall, and front&back. Meshing is done by keeping more cell concentrations in the step area. This is done to provide a better catch of turbulent flow in this region. The boundary conditions at the inlet are 'constant velocity profile', 'zero gradients' at the outlet, and 'wall (no-slip)' in the lower and upper wall areas.

Numerical simulation in this study was carried out with a Reynolds number of 36000. The equation governing the flow in the Backward Facing Step is given by the Reynolds Averaged Navier-Stokes equation [9] which is given by Equation (1).

$$\bar{u}_j \frac{\partial \bar{u}_i}{\partial x_j} - \frac{\partial}{\partial x_j}\left[v_{eff}\left(\frac{\partial \bar{u}_i}{\partial x_j} + \frac{\partial \bar{u}_j}{\partial x_i} \right)\right] = -\frac{\partial p}{\partial x_i} \tag{1}$$

The turbulence model used in this numerical simulation is k-omega Shear Stress Transport (SST) [10]. The advantage of the k-omega SST Turbulence Model is that it has good capabilities in the area around the wall. The equation for the specific turbulence dissipation rate is given by equation (2).

$$\frac{D}{Dt}(\rho\omega) = \nabla \bullet (\rho D_\omega \nabla \omega) + \frac{\rho\gamma G}{v} - \frac{2}{3}\rho\gamma\omega(\nabla \bullet u) - \rho\beta\omega^2 - \rho(F_1 - 1)CD_{k\omega} + S\omega \tag{2}$$

The equation for turbulent kinetic energy is shown by equation (3) and the turbulence viscosity is obtained by using equation (4).

$$\frac{D}{Dt}(\rho k) = \nabla \bullet (\rho D_k \nabla k) + \rho G - \frac{2}{3}\rho k(\nabla \bullet u) - \rho\beta^*\omega k + S_k \tag{3}$$

$$vt = a_1 \frac{k}{max(a_1\omega, b_1 F_{23} S)} \tag{4}$$

The solver used in this simulation is SIMPLEFOAM. SimpleFoam is a solver for incompressible turbulent flow, using the SIMPLE (Semi-Implicit Method for Pressure Linked Equations) algorithm. Where the SIMPLE method is used to solve equation (5).

$$\nabla \bullet u = 0 \tag{5}$$

$$\nabla \bullet (u \otimes u) - \nabla \bullet R = -\nabla p + S_u \tag{6}$$

Equation (6) is the momentum equation. Where u is speed, p is the kinematic pressure, R is the stress tensor, S_u and is the momentum source.

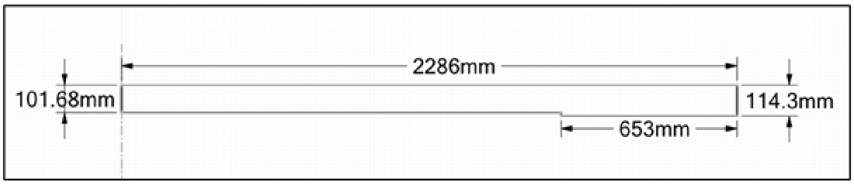

Figure 1. Geometry of BFS

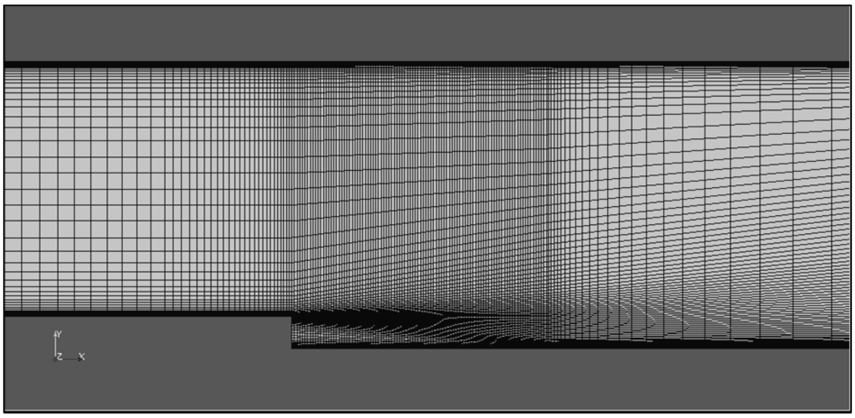

Figure 2. Meshing area of the step region

2.2 Machine Learning Method

Numerical simulation results using OpenFoam® are plotted into CSV form. Three machine learning models were selected to make predictions. The machine learning models used are Multi-Layer Perceptron, RandomForrest Regressor, and Multiple Linear Regression. The plotted dataset is split into two parts. As much as 80% is used as a data train for machine learning, and the remaining 20% is used as a data test.

Table 1. Parameter MLP

No.	Parameter	Value
1	number of hidden layers	25
2	number of nodes per hidden layer	100
3	activation function	Swish
4	loss function	MSE (Mean squared error)
5	optimization algorithm	Adam
6	learning rate	2.5×10^{-6}
7	batch size	10
8	L^2 penalization coefficient	0
9	weight initialization function	Xavier normal
10	patience for early stopping	30

Multi-Layer Perceptron (MLP) is the most widely used model in artificial neural network applications using back-propagation training algorithms. The definition of architecture in the MLP network is a very relevant point because the lack of connection can make the network unable to solve the problem of non-adjustable parameters, while excess connections can cause over-fitting of the training data [11].

Table 2. RandomForrest Parameter Parameters

No.	Parameter	Value
1	n_estimators	1000
2	criterion	mse
3	max_depth	5
4	min_samples_split	2
5	min_samples_leaf	1
6	random_state	5

Table 3. Parameters of Multiple Linear Regression

No.	Parameter	Value
1	fit_intercept	true
2	normalize	true
3	copy_X	true
4	n_jobs	none
5	random_state	0
6	positive	false

3. Result and Discussion

Post-processing of numerical simulation data is carried out in ParaView software. The extracted data are Cp and Cf in the area around the lower wall based on equation (7) and (8).

$$Cp = \frac{P - P_\infty}{\frac{1}{2}\rho U_\infty^2} \tag{7}$$

$$Cf = \frac{\tau_w}{\frac{1}{2}\rho U_\infty^2} \tag{8}$$

Where P_∞ is the free-stream pressure (0Pa), P is the local pressure at the point (Pa), ρ is the density of the air (1.225 kg/m^3), U_∞ is the free-stream velocity (m/s), and τ_w is the local wall shear stress at the point (Pa).

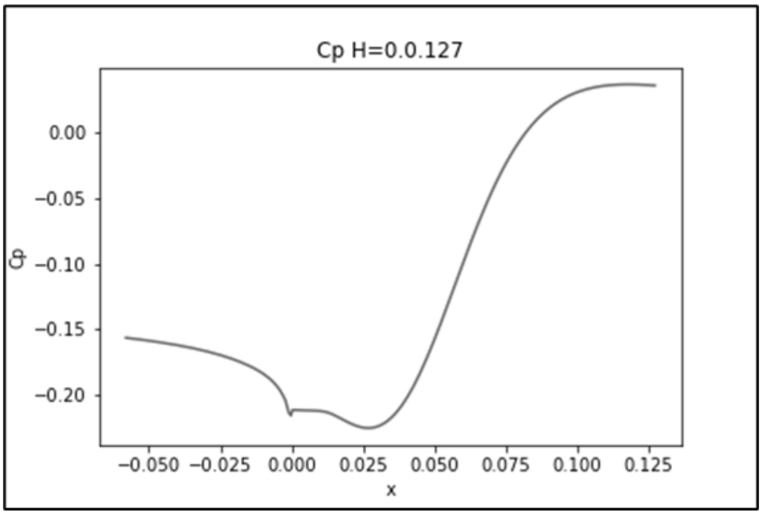

Figure 3. Cp H=12.62 mm

The re-attachment length is determined by the point where the Cp value begins to decrease from its maximum value or the point where the curve intersects the line along with the origin of the Y-axis (Cf).

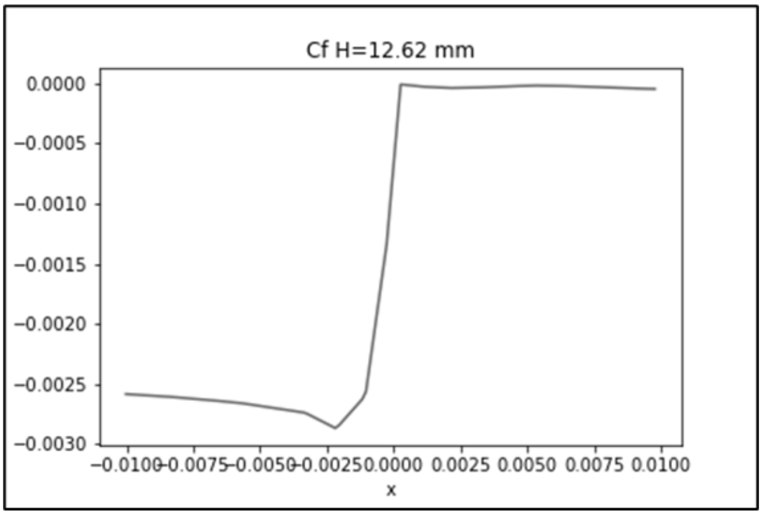

Figure 4. Cf H=12.62 mm

In machine learning section, accuracy tests are carried out on each machine learning model used. Obtained for each accuracy value from the machine learning model as follows:

Table 4. The value of machine learning model accuracy

No.	Model	Value
1	Multi-Layer Perceptron	-101.5%
2	RandomForrest Regressor	96%
3	Multiple Linear Regression	99%

Based on the results of the accuracy test, in this study, predictions will be made using a machine learning model with the highest accuracy value, namely the Multiple Linear Regression model. The value of the model has a positive trend towards the test data shown in Figure 5.

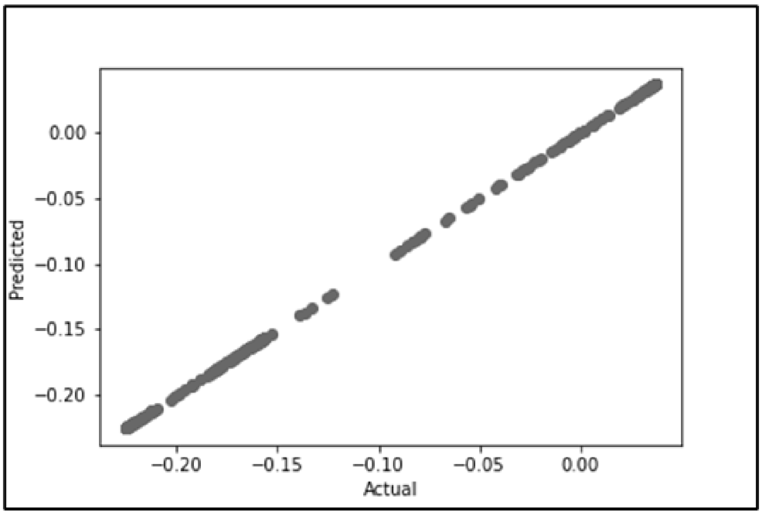

Figure 5. Distribution of predicted and actual data H=12.62 mm

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However, the variation of BFS with a separation height of 9.465 mm, 6.31 mm, and 3.155 mm is predicted using the model that has been obtained. The obtained for Cp for each step height variation are as shown in Figure 6, and Cf in Figure 7.

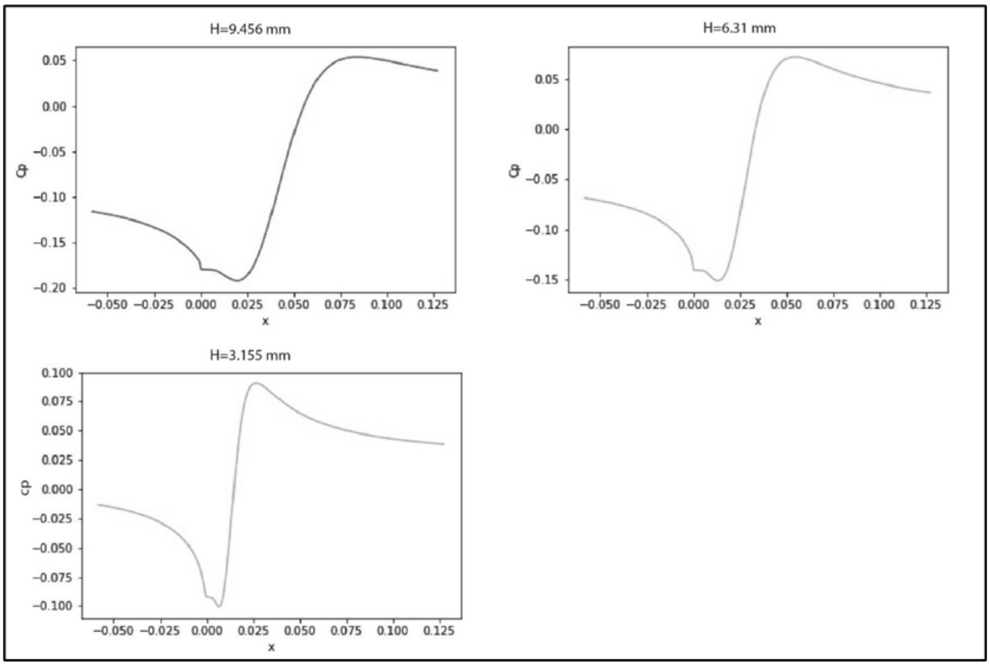

Figure 6. Cp BFS step with a height of 9,465 mm, 6.31 mm, and 3,155 mm predicted results

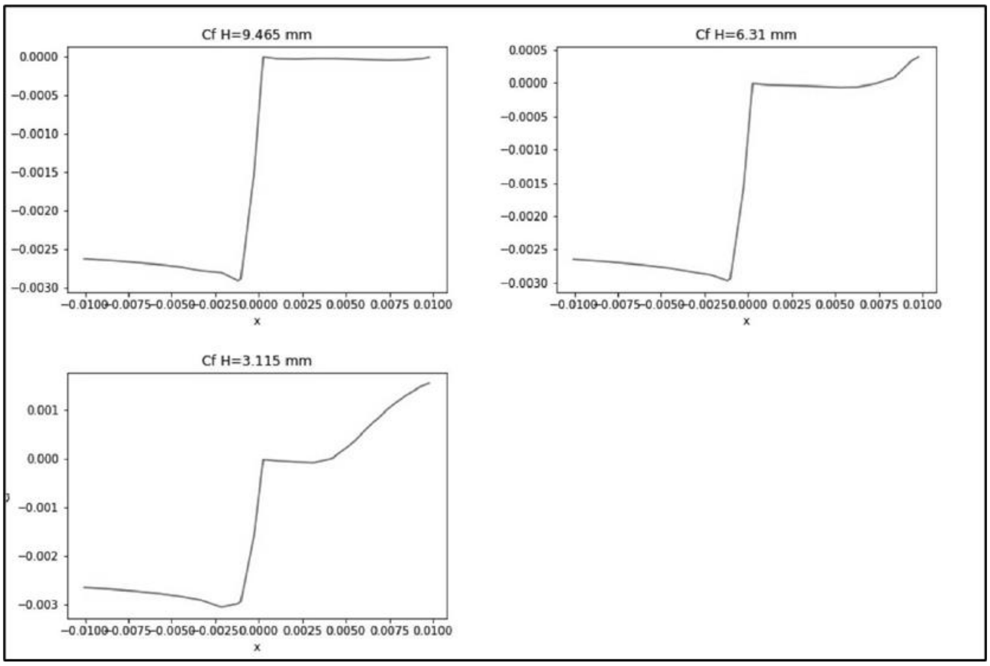

Figure 7. Cf BFS step 9,465 mm, 6.31 mm, and 3,155 mm prediction results

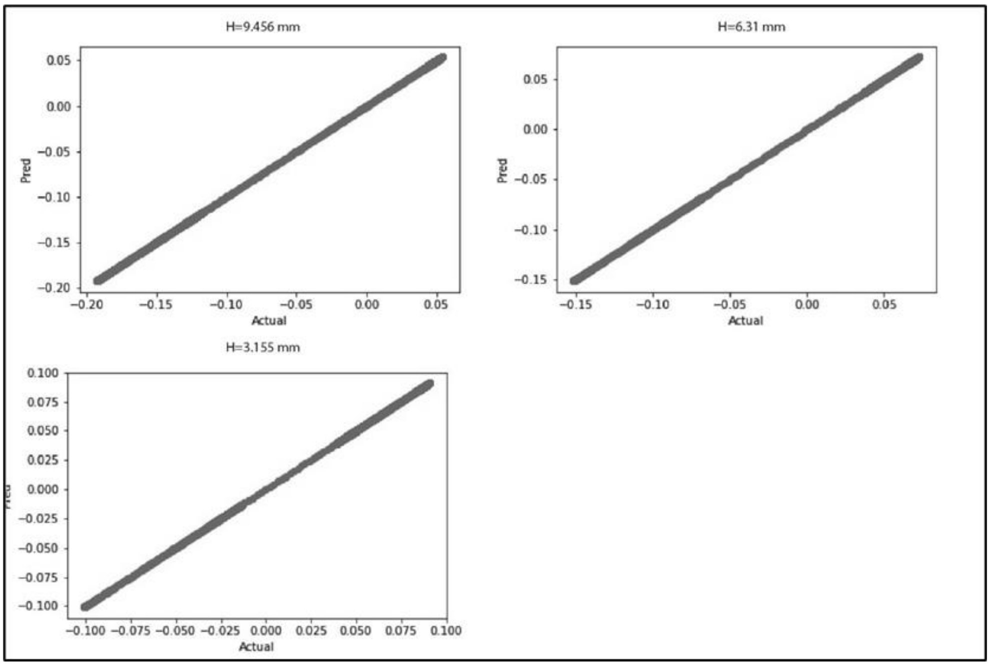

Figure 8. Distribution of predicted and actual data

4. Conclusion

Numerical simulations of BFS were performed in OpenFoam® software using the k-omega Shear Stress Transport (SST) turbulence model. Simulations were carried out on the Reynolds number of 36000 with the solver used was SIMPLEFOAM. The numerical simulation data is plotted into CSV form which is then used as a dataset for machine learning. In the machine learning section, 3 models were selected, namely Multi-Layer Perceptron, RandomForrest Regressor, and Multiple Linear Regression to predict Cp and Cf from the BFS variation with separation heights (steps) of 9,465 mm, 6.31 mm, and 3,155 mm using a numerical simulation dataset that has been done. The results of the accuracy test show that Multi-Layer Perceptron has an accuracy value of -101.5%, 96% for RandomForrest Regressor, and 99% for Multiple Linear Regression. With the highest accuracy value, Multiple Linear Regression was chosen to make predictions. The results show that the predicted value has a positive trend and is identical to the actual according to Figure 8. Thus, the machine learning model used in this study is said to be able to predict and reconstruct information from BFS turbulence from numerical simulation results.

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