PREDICTION OF DRAG REDUCTION EFFECT IN TURBULENT PULSATING PIPE FLOW BY MACHINE LEARNING BASED ON EXPERIMENTAL DATA

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ABSTRACT

The drag reduction effect of pulsation in turbulent pipe flow was predicted by machine learning based on experimental data. In the experiment, we measured 2498 types of pulsating flows generated by randomly setting the way of acceleration, deceleration, and period. The average drag reduction rate was 19% with a maximum of 39%. A machine learning model which is suitable for time-series is trained to predict bulk flow velocity and differential pressure to calculate the drag reduction rate. The pressure gradient is predicted over a wider range than that in the previous study. The correlation coefficients between the experimental results and prediction results were over 0.9. The predicted drag reduction ratio was 2.3% lower than the experimental results on average with an RMSE of 6.3%.

BACKGROUND AND OBJECTIVE

Skin friction drag reduction by control of turbulent flow is important for various fields in terms of saving energy. One of the effective ways to reduce the skin friction drag is an active control to accelerate the flow. It has been observed that the accelerated flow reduces the wall shear stress by relaminarization (Shuy, 1996; Greenblatt and Moss, 1999). The drag reduction effect of pulsating flow, which repeats acceleration and deceleration periodically, has been also investigated. In an experiment, the skin friction drag in pulsating pipe flow was reduced by 63% compared to corresponding steady flow (Souma et al., 2009). However, due to a large degree of freedom for acceleration and deceleration patterns, pulsation in turbulent pipe flow has not been optimized.

Machine learning has been introduced in the field of fluid mechanics to deal with problems involving combinations of many parameters. In the latest study, the voltage input to a centrifugal pump was changed with time to generate over 7000 types of pulsating flows in a pipe and the machine learning was performed by using long short-term memory (LSTM) which is suited to predict time-series data (Kobayashi et al., 2021). As a result, the time response of the bulk flow velocity and the differential pressure to the voltage input to the pump was predicted and the drag reduction effect was also predicted with high accuracy. However, the drag reduction effect of pulsating flow at high pressure gradients has not been sufficiently investigated because of the limitation of the pump specification.

The purpose of our study is to develop a predictive model of the drag reduction effect of pulsation in turbulent pipe flow over a wide range of pressure gradients. In the present study, we examined the drag reduction effect of various types of pulsating flows and performed machine learning based on experimental data.

METHOD

Experimental method

A schematic of experimental apparatus is shown in Fig. 1. It consists mainly of acrylic pipe with inner diameter d = 19.5 mm. The radius of the bend is R = 250 mm. The length of the entrance section is 1000 mm to develop turbulent flow. The length of the test section is l = 2000 mm, and the differential pressure Δp between upstream and downstream edges of the test section is measured by differential pressure gauge (EJX110J, Yokogawa Electric co. ltd). Bulk flow velocity u_b and temperature are measured by an electromagnetic flowmeter (LF410, Toshiba Infrastructure systems & Solution co.) and thermocouple (HTK0226, Hakko Electric co.) respectively which are installed downstream side of the test section. The working fluid is water. Gear pumps (TG-30S-PU-EB-KA, Tsukasa electric co.) are adopted to generate pulsating flow with rapid flow velocity changes. To make a sufficient flow rate, a set of the five gear pumps are connected in parallel and driven synchronously.

By changing the voltage input to the pumps with time, the flow velocity changes, and thus a pulsating flow is generated. To measure the drag reduction effect of various pulsating flows with different acceleration and deceleration intensities and pulsation period, the following procedure was conducted to generate the input voltage waveform to the pumps. Figure 2 shows an example of input voltage waveform to the pumps. The voltage waveforms were generated using spline interpolation to smooth out changes in flow velocity and pressure gradient to improve prediction accuracy. In addition, the fact that the pressure gradient does not change abruptly has advantages from a practical perspective. First, pulsation period T is set randomly to 4-20 sec. Second, 3-7 control points at 1-6 V are set. The first and last control points are set to the same voltage. Third, control points are connected by cubic periodic spline interpolation. Finally, voltage waveforms were generated when the following conditions are fully met; all voltage values were in the range of 1-6V, the maximum voltage gradient was under 3 V/s, and the mean voltage corresponds to bulk Reynolds number Re_b = 3400-3800. Voltage to the pumps was input at 50 ms interval. 2498 types of pulsating flows are investigated.

Friction drag is evaluated by friction coefficient C_f which is calculated as

$$C_f = \frac{\tau_w}{\frac{1}{2}\rho u_b^2} = \frac{\frac{d}{4}\left(\frac{\Delta p}{l} - \rho \frac{du_b}{dt}\right)}{\frac{1}{2}\rho u_b^2} \tag{1}$$

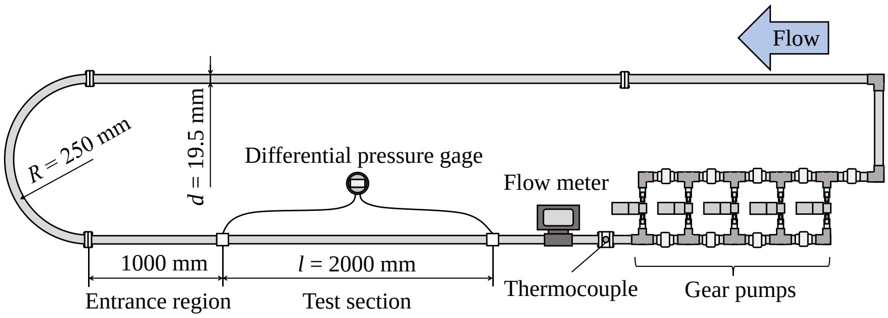


Figure 1. Schematic of experimental apparatus.

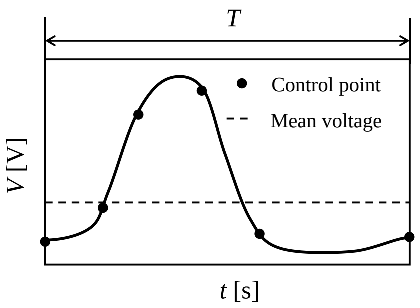


Figure 2. An example of pump voltage.

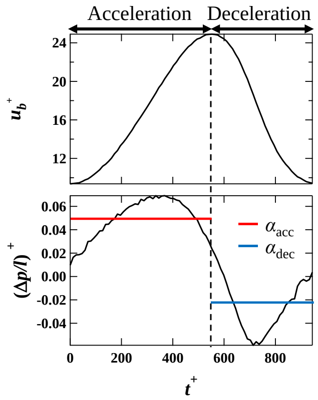


Figure 3. Examples of changes in bulk flow velocity and pressure gradient.

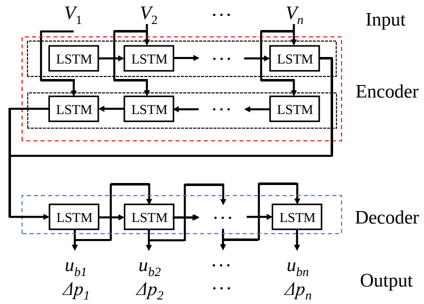


Figure 4. Schematic of network structure.

where τ_w is the wall shear stress. Drag reduction rate R_D is defined as

$$R_D = \frac{C_{f,\text{ Blasius}} - [C_f]_T}{C_{f,\text{ Blasius}}} \times 100 \tag{2}$$

where $C_{f,\text{ Blasius}}$ represents a value of the empirical formula provided by Blasius. The bracket $[\ ]_T$ represents the time-averaged value.

As shown in Fig. 3, the pressure gradient is defined in two sections, one for acceleration where the velocity increases, and the other for deceleration where the velocity decreases. The pressure gradient parameter α_{acc} is defined as

$$\alpha_{\text{acc}} = \left(\frac{\Delta p}{l}\right)^+_{\text{acc}} \tag{4}$$

where superscript $^+$ represents non-dimensionalization by friction velocity u_τ and kinetic viscosity ν, and subscript $_{\text{acc}}$ represents averaged value during the time where the flow is accelerated within a period. Relaminarization is found to occur when α>0.018(Patel and Head, 1968).

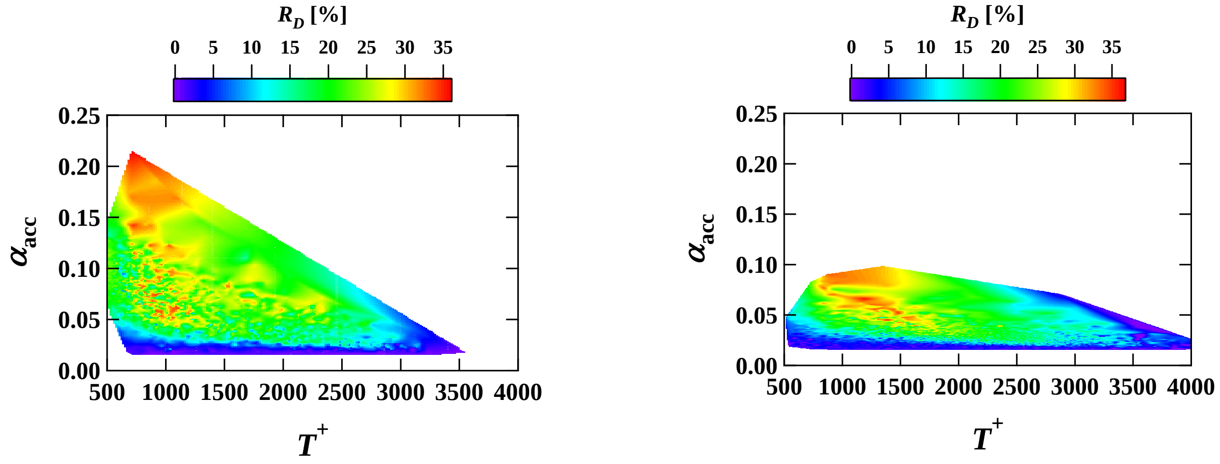
Machine learning

The sequence-to-sequence model is used for machine learning which is shown in fig. 4. It is the same model used in the previous study which has shown to be superior in prediction accuracy to the multilayer perceptron model (Kobayashi et al., 2021). LSTM which is used in this model is a type of recurrent neural network that can learn time-series data for long-term dependence. It consists of an encoder that converts time-series data into a feature vector and a decoder that converts it into other time-series data. The encoder has two layers of LSTMs in the forward direction and backward direction. The decoder has two layers of LSTMs in the forward direction. In this model, input data is pump voltage, and output data are time-series data of flow velocity and differential pressure. In other words, time changes in flow velocity and differential pressure are predicted from pump voltage. Then, the drag reduction rate is calculated from eq. (1) and eq. (2).

Adamax method is used as an optimizer to update the weights. 1998 cases, that is 80% of all cases, are selected as training data set randomly. 500 cases, that is 20% of all cases, are selected as validation data set randomly. Training data set is used to fit the parameters of the model. Validation data set is used for the evaluation of a model fit on the training data set.

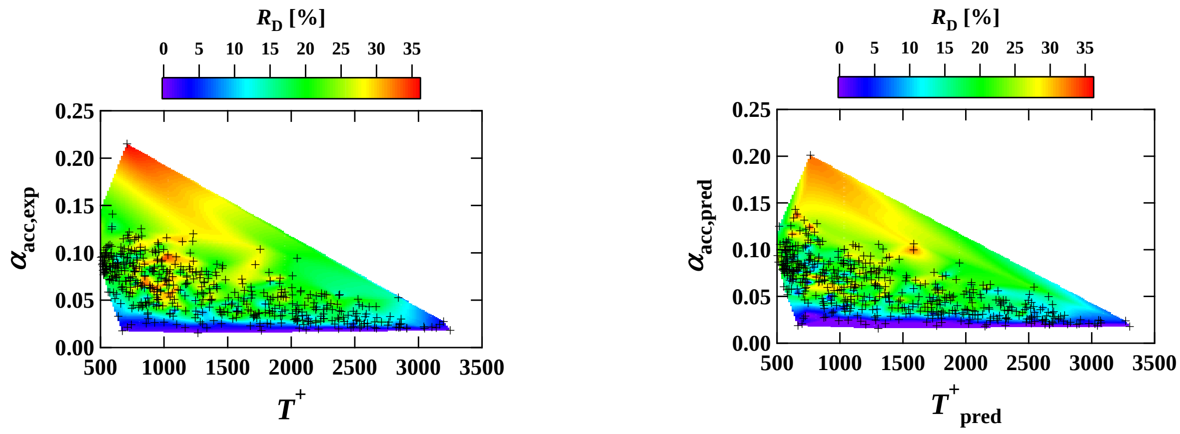
RESULTS

The present result of drag reduction effect upon pressure gradient during acceleration and pulsation period from 2498 types of pulsating flows is shown in Fig. 5(a). The maximum drag reduction rate is R_D = 39% at α_{acc} = 0.11 and T^+ = 740.



(a) (b)

Figure 5. Distribution of drag reduction rate upon pressure gradient during acceleration and pulsation period: (a) present results; (b) previous results(Kobayashi et al., 2021).



(a) (b)

Figure 6. Distribution of drag reduction rate upon pressure gradient during acceleration and pulsation period: (a) experiment (validation data); (b) prediction.

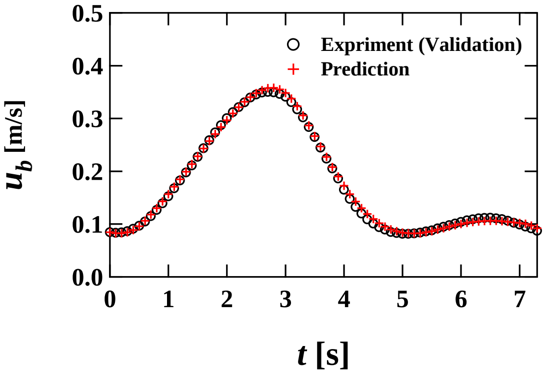
Regardless of the pulsation period, little drag reduction effect is achieved when $\alpha_{acc} < 0.02$. This is due to weak acceleration and lack of relaminarization. Many cases of $R_D > 30\%$ were observed at $\alpha_{acc} > 0.05$ and $700 < T^+ < 1200$. The sparsity of the distribution indicates that just the pulsation period and the mean pressure gradient during acceleration are unable to determine the drag reduction rate. Figure. 5(b) shows the results of the previous study (Kobayashi et al., 2021). Due to the quick acceleration of the gear pumps, the maximum value of α_{acc} is 0.22, which is larger than 0.10 in the previous study. The overall trend is similar. However, the distributions do not match accurately because each pulsating flow has different combinations of acceleration and deceleration.

Figure 6(a) shows the distribution of the drag reduction rate of validation data. A counterpart of Fig. 6(a) predicted by the present machine learning model is depicted in Fig. 6(b). Prediction results are expressed based on α_{acc}, T^+ and R_D predicted from the respective validation data. The overall trends of drag reduction rate between experimental results and prediction results are similar.

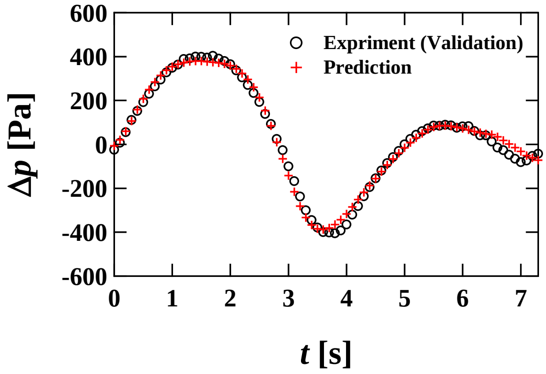
Figure 7 shows a representative example of predicting the time change of flow velocity and pressure gradient. The prediction result of bulk flow velocity is close to the experimental results. The Pressure gradient, which is difficult to predict due to its low linearity with flow velocity, is also predicted well. In the validation data, the mean pressure gradient during acceleration of the validation data is $\alpha_{acc} = 0.10$, the pulsation period is $T^+ = 770$, and the drag reduction rate is $R_D = 35\%$. On the other hand, because of errors in the mean values of flow velocity and pressure gradient compared to the experimental results, the prediction results were $\alpha_{acc} = 0.09$, $T^+ = 830$, and $R_D = 31\%$.

To evaluate the accuracy of the prediction of flow velocity and differential pressure, the correlation coefficient R is calculated from the following equation;

$$\mathrm{R} = \frac{\frac{1}{n}\sum_{i=1}^{n}\left(X_{i,\mathrm{pred}}-\overline{X_{\mathrm{pred}}}\right)\left(X_{i,\mathrm{exp}}-\overline{X_{\mathrm{exp}}}\right)}{\sigma_{\mathrm{pred}}\sigma_{\mathrm{exp}}} \quad (5)$$



(a)



(b)

Figure 7. A representative example of prediction by machine learning: (a) bulk flow velocity; (b) pressure gradient.

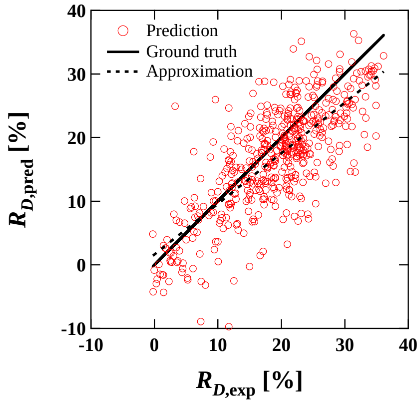


Figure 8. Prediction results of drag reduction rate.

Table 1. Error of each parameter in validation data.

Parameter	R	CV
Flow velocity	0.992	0.0143
Differential pressure	0.977	0.0830

Here, X represents either flow velocity or differential pressure, σ represents their standard deviation, and n represents the number of data points of each waveform. Coefficient of variation CV is calculated based on the following definition;

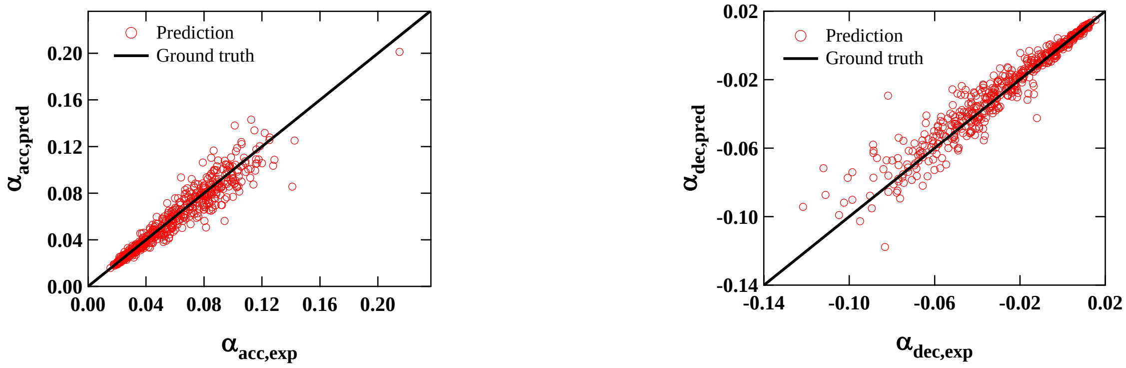
$$\mathrm{CV} = \frac{\mathrm{RMSE}_X}{\overline{X}} \tag{6}$$

Here, RMSE_X represents the root mean square errors of either flow velocity or differential pressure, and the superscript bar means averaged value.

Table 1 shows correlation coefficients and coefficient of variation between the experimental value and predicted value of flow velocity and differential pressure. The calculated correlation coefficients are over 0.9 for both flow velocity and differential pressure, confirming high correlation between experimental results and prediction results. These results are comparable to the R = 0.991 for flow velocity and R = 0.979 for differential pressure in the previous study (Kobayashi et al., 2021). Thus, high prediction accuracy is kept even though the rapid change in flow velocity and differential pressure due to new pumps. On the other hand, a comparison of the respective CV values shows that the CV of differential pressure is more than five times larger than the CV of flow velocity. This is because differential pressure is nonlinear and more difficult to predict than flow velocity.

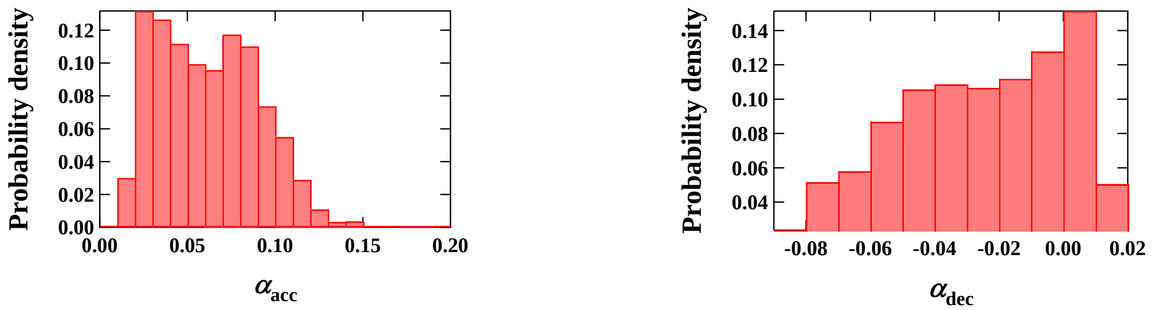
Figure 8 shows the relationship between experimental results and prediction results of drag reduction rate. The solid line represents the case of correct prediction, and the dashed line is the regression line of the prediction results. The overall trend is predicted. Predicted drag reduction rate was on average 2.3% lower than the experimental results. RMSE of drag reduction rate is also calculated to evaluate the mean variation. RMSE is calculated based on the following definition;

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_{i,\,\mathrm{pred}} - \overline{x_{i,\,\mathrm{exp}}}\right)} \tag{7}$$



(a) (b)

Figure 9. Prediction of pressure gradient: (a) acceleration; (b) deceleration.



(a) (b)

Figure 10. Probability density of pressure gradient: (a) acceleration; (b) deceleration.

As a result, the value of 6.3% is obtained whereas 3.8% is in the previous study (Kobayashi et al., 2021). This is because machine learning was performed on more than 7000 data of pulsating flow with slow acceleration and deceleration, which means little change in flow velocity and differential pressure, in the previous study. Thus, the increase in the RMSE value may be related to the large variation in flow velocity and differential pressure and the number of training data.

Figure 9 shows the predicted pressure gradient during acceleration and deceleration. In both cases, the error tends to increase as the absolute value increases. This is due to the difficulty of predicting waveforms that change more rapidly and the lack of training data for these waveforms. Figure 10 shows the probability densities of the pressure gradient during acceleration and deceleration for all measured data. Since there are few data with large absolute values, there is a possibility to improve the prediction accuracy by increasing such data.

CONCLUSIONS

To develop a predictive model of the drag reduction effect by machine learning, 2498 types of pulsating flows in a pipe with various periods and acceleration/deceleration were investigated in the experiment. Using those experimental data as training data, machine learning based on sequence-to-sequence model with LSTM was also performed.

In the experiment, we measured drag reduction rate of R_D = 39% at α_{acc} = 0.11 and T^+ = 740. maximum average pressure gradient during acceleration of α_{acc} = 022, which is larger than the previous study. The average drag reduction rate for all cases was 19%.

By performing machine learning, time-series data of flow velocity and differential pressure were predicted from input voltage to the pumps. Drag reduction rates which are calculated from them captured the trend of experimental results. The predicted drag reduction rate was 2.3% lower than the experimental results on average with an RMSE of 6.3%.

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