Modelling cycle-to-cycle variations

Luca Damiola

12 March 2023

1 Introduction

For this analysis, experimental fluid dynamics data from the wind tunnel are used. The selected test case consists of a sinusoidal motion (offset = 16°, amplitude = 6°, frequency = 1 Hz) which presents relevant cycle-to-cycle variations, as shown in Fig. 1. This dataset contains 40 cycles, but the first one has been discarded to remove the initial transient. Therefore, a total of 39 cycles is considered, corresponding to a total number of sample points equal to 7800 (sampling frequency f_s = 200 Hz).

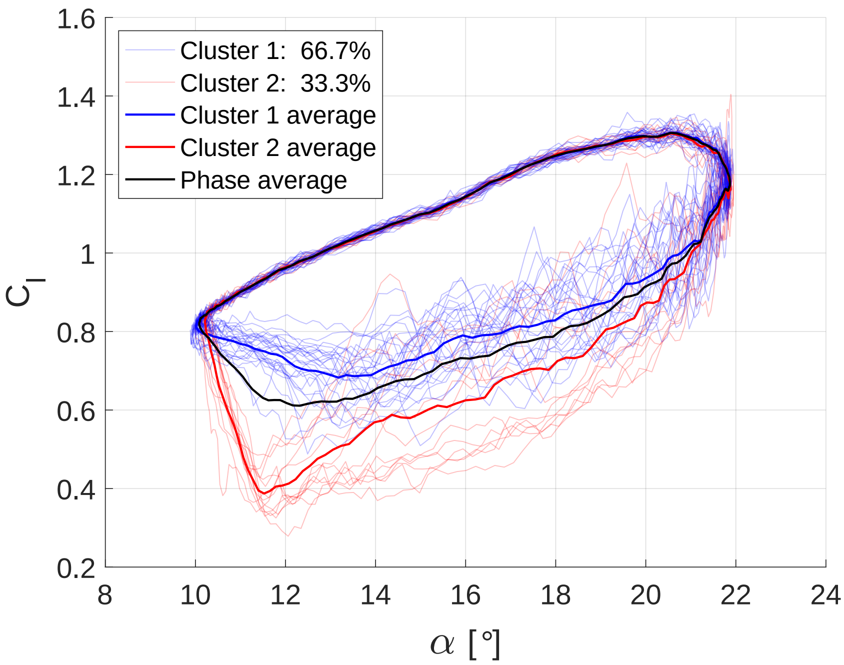

Figure 1: Two different clusters are identified and compared to the phase-averaged curve evaluated over all the available cycles.

2 Kalman Filter to enhance SS-NN model predictions

2.1 Application 1: Training data is too limited

Regardless of the model complexity, if the training data is too limited the SS-NN model is not able to accurately predict cycle-to-cycle variations. In our specific application, $N = 7$ cycles (out of the available 39) have been used to train the SS-NN model. The remaining 32 cycles have been kept for model validation. As illustrated in Fig. 2, such a model fails in predicting the cycle-to-cycle variability. On the other hand, for a number of training cycles $N \geq 10$, the SS-NN model predictions are accurate and capture well the evolution of the lift coefficient, Fig. 3.

Task: Implementation of a Kalman Filter to enhance model predictions. The Kalman Filter will assimilate the model output with some scattered lift measurements. The goal is to predict the cyle-to-cycle variations by adding the minimum amount of information (the scattered lift measurements).

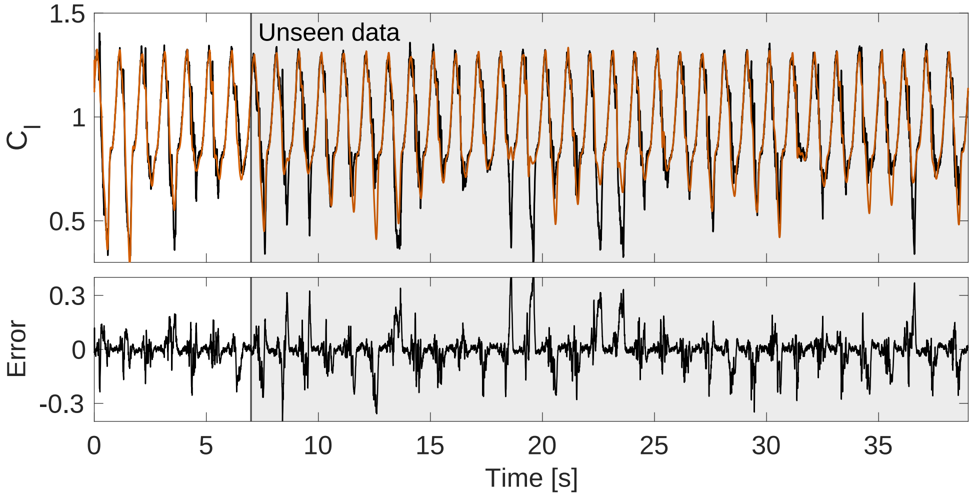

Figure 2: The SS-NN model (orange line) is trained using 7 periods and validated on the remaining 32 periods. The input signal is the real measured angle of attack. The error is defined as $C_{l\,\text{model}}(t) - C_{l\,\text{exp}}(t)$.

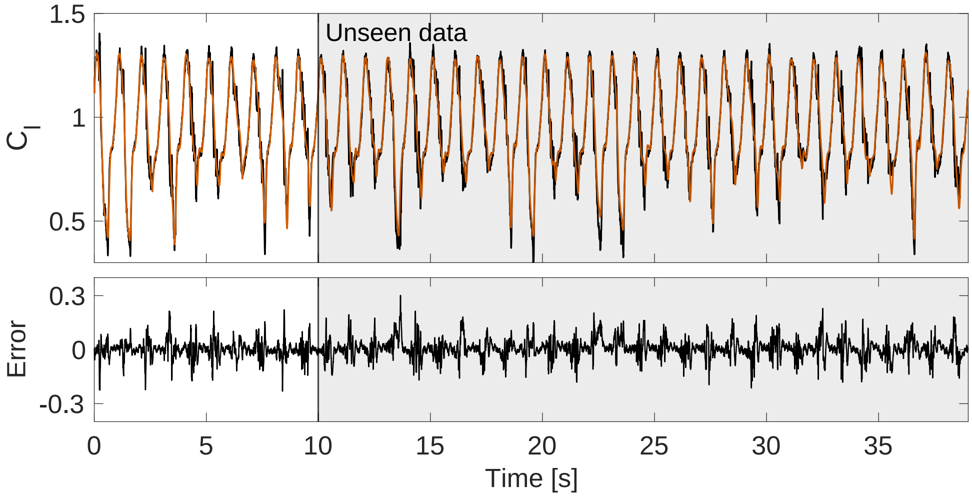

Figure 3: The SS-NN model (orange line) is trained using 10 periods and validated on the remaining 29 periods. The input signal is the real measured angle of attack. The error is defined as $C_{l\,\text{model}}(t) - C_{l\,\text{exp}}(t)$.

2.2 Application 2: No information is available regarding the real input signal

In the previous section, the SS-NN models have been trained using the measured lift coefficient (output signal) and the measured angle of attack (input signal).
What happens if we don't have information regarding the real angle of attack of the aerofoil?
Let's assume that, for some reason, we cannot measure the real angle of attack, but we just know the approximate angle of attack range (in our specific example, we know that the aerofoil is sinusoidally pitching between $\alpha_{\text{min}} = 10°$ and $\alpha_{\text{max}} = 22°$ at a frequency $f = 1$Hz). However, we have a measurement system that measures the lift at every time instant. We can train a SS-NN model using the measured lift coefficient (output signal) and an ideal sinusoidal motion (input signal). Regardless of the number of periods used for training, this model will always provide an "averaged" estimate of the lift coefficient and it will not distinguish one cycle from the others (see Fig. 4 and Fig. 5).

Task: Let's assume that, in the grey region depicted in the figures, we have some scattered lift measurements. Can we integrate this extra information using a Kalman Filter in order to enhance model predictions? Similarly to 'Application 1', the Kalman Filter will assimilate the model output with some scattered lift measurements. The goal is to predict the cyle-to-cycle variations by adding the minimum amount of information (the scattered lift measurements).

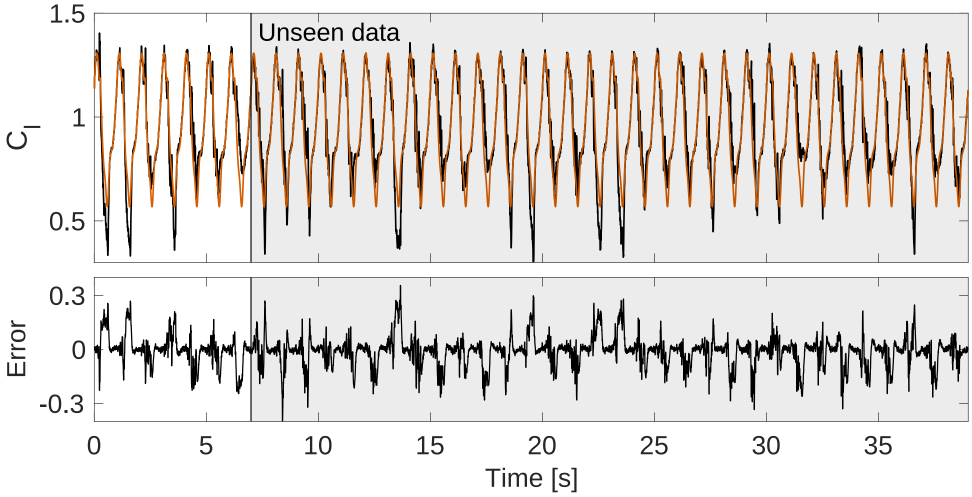

Figure 4: The SS-NN model (orange line) is trained using 7 periods and validated on the remaining 32 periods. The input signal is an ideal sinusoidal motion. The error is defined as $C_{l_{\text{model}}}(t) - C_{l_{\text{exp}}}(t)$.

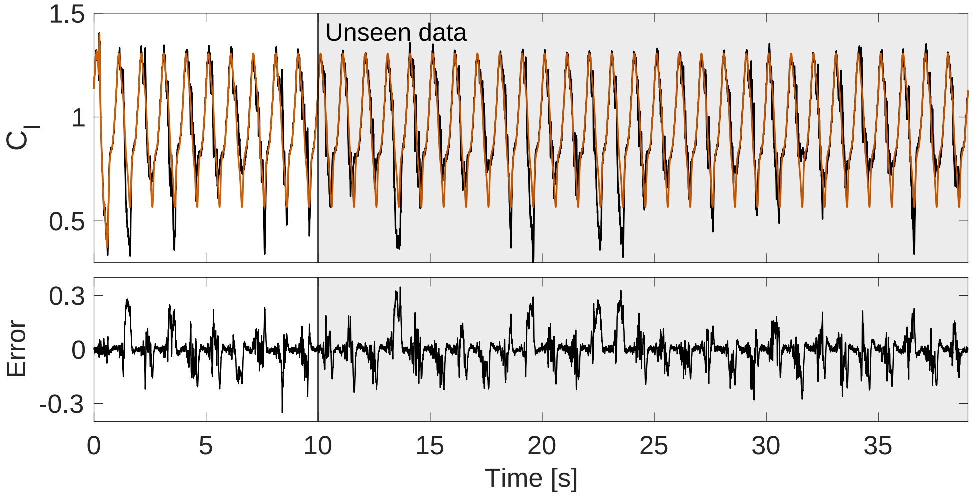

Figure 5: The SS-NN model (orange line) is trained using 10 periods and validated on the remaining 29 periods. The input signal is an ideal sinusoidal motion. The error is defined as $C_{l_{\text{model}}}(t) - C_{l_{\text{exp}}}(t)$.