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Demonstration of model-based real-time anomaly detection in a JAXA 6.5m×5.5m low-speed wind tunnel.

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Abstract

In this study, real-time anomaly detection in a wind tunnel was conducted using a threshold based on uncertainty quantification of a numerical model. A model-based numerical model of a wind tunnel was developed, and the uncertainty consisting of input uncertainty, model form uncertainty, and numerical approximation was quantitatively evaluated. The threshold of anomaly obtained here was demonstrated in a 6.5m×5.5m wind tunnel of Japan Aerospace Exploration Agency (JAXA). Synthetic anomaly injected into the measurement system was successfully detected.

1. Introduction

In large-scale satellite constellation projects, the number of satellites to be operated drastically increases. Conventional operations of satellites relying on expert knowledge could not cope with such a situation. Thus, the development of operational technology to achieve more efficient and low-cost operations is an urgent task. To reduce the operational cost, autonomous operations not relying on expert knowledge is essential, but such new technologies should be demonstrated where trial and error is acceptable before being applied to mission-critical systems such as spacecraft. This study focused on the 6.5m × 5.5m wind tunnel in Japan Aerospace Exploration Agency (JAXA), called LWT1, which has been operated manually for over 60 years. To achieve autonomous operation in LWT1, Prognostics, and Health Management (PHM) methodology are developed and demonstrated. (Tahan, Tsoutsanis, Muhammad, and Abdul, 2017, Kandukuri, Kalusen, Karimi, and Robbersmyr, 2016, Wang, Tsui, and Miao, 2018) Generally, when performing anomaly detection in a system, the normal space of the system is determined by a large amount of normal data by using a data-driven approach. However, in the wind tunnel, the wind tunnel model has a wide variety depending on the user of the wind tunnel, leading to the difficulty to determine the normal space of the wind tunnel by using a data-driven approach. In this study, the model-based numerical model of the wind tunnel has developed, and the normal space for anomaly detection has been determined by the results of Uncertainty Quantification (UQ) of the numerical model. This paper reports the demonstration of real-time anomaly detection by using the UQ results of the model-based numerical model as the normal space in LWT1.

2. LWT1

Figure 1 shows an overview of LWT1, which is a 200 m closed-circuit wind tunnel capable of generating flow from 1 m/s to 70 m/s with a 9.3 m diameter fan. Detailed information on LWT1 is available in the literature (Shigemi & Hirooka, 1967).

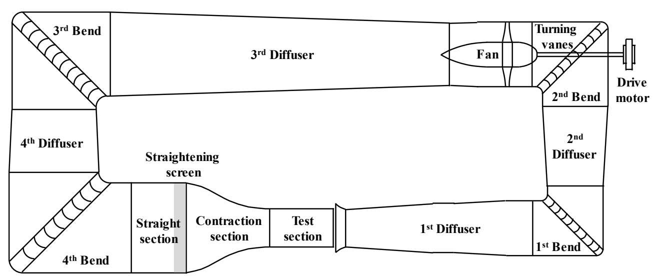

Figure 1. Overview of LWT1

A Pitot velocimetry is installed in the test section to measure wind velocity. An anomaly of leakage from the pressure tube is one of the failure modes in LWT1, resulting in an underestimation of wind velocity. In the demonstration of anomaly detection, this anomaly was produced by installing a needle value with a flowmeter in the total pressure tube of the pitot velocimetry. The rotational speed of the fan was fixed at 181 rpm. A general aircraft model (NASA Common Research Model, CRM) was used as a wind tunnel model (Levy, Laflin, Tinoco, Vassberg, Mani, Rider, Rumsey, Wahls, Morrison, Brodersen, Crippa, Mavriplis, and

Murayama, 2014, Koga, Kohzai, Ueno, Nakakita, and Sudani, 2013). The angle of attack was fixed at 0 degrees.

3. NUMERICAL MODEL OF LWT1

Because of the variety of shapes of wind tunnel models depending on users, training data of both normal and anomaly states does not exist in advance. To overcome this challenge, this study developed a numerical model, and then, evaluated the uncertainty of the numerical result by UQ. The uncertainty represents the normal space of the target system. The model-based numerical model of LWT1 was developed for real-time anomaly detection. Flow ducts were modeled by straight ducts with quasi-one-dimensional assumptions and diffusers based on an empirical model (Idelchick, 1996). Major sources of pressure loss are the 1st, 2nd, and 3rd bends with guide vanes, and straightening screen in front of the test section, and a wind tunnel model. They are modeled by the quasi-one-dimensional orifice. The modeling of the fan was based on a fan map obtained experimentally. Given the rotational speed, the pressure head is determined. (Hamato, Tsutsumi, Yamashita, Shiohara, Hirotani, and Kato, 2021). This study employed AMESIM (Siemens Co.) in which the Bond graph method was used to connect these models.

4. UQ

By conducting UQ, it is possible to quantitatively estimate the uncertainty of numerical models resulting from computational errors and uncertainty of model parameters. This study employed UQ framework proposed by Roy and Oberkampf (2011). In this method, the uncertainty of the numerical model is evaluated in the following steps.

1. Identify the objective variables (System Response Quantity, SRQ), and the uncertainty of explanatory variables are classified into epistemic and aleatory uncertainties. Epistemic uncertainty comes from the lack of knowledge and information about the model or explanatory variables. It can be reduced by accumulating knowledge and information through experimental measurement, for example. Uncertainty whose probabilistic distribution is unclear because of insufficient information is classified as epistemic uncertainty, and in such cases, the probabilistic distribution of epistemic uncertainty is modeled as uniform distribution. On the other hand, aleatory uncertainty comes from the variance in time and space of variables. It is difficult to reduce aleatory uncertainty because its variability is the nature of variables. The probabilistic distribution of aleatory uncertainty is modeled as Gaussian distribution, for example (Ogata, 2009).
2. Evaluate the propagation of input uncertainties to the objective variables. For epistemic uncertainty, Latin Hypercube Sampling (LHS) is often used to make samples. For aleatory uncertainty, Monte-Carlo (MC) method is used. These samples are given to the numerical model to calculate the objective variables. The probabilistic distribution of the objective variables can be obtained.
3. Evaluate the model form uncertainty which corresponds to the difference between the experimental and numerical results. The difference is called validation. The model form uncertainty is evaluated by calculating the expectation of difference between the probabilistic distributions of the experimental and numerical results.
4. Evaluating the error comes from numerical calculations, which is called numerical approximation. This includes rounding error, discretization error, and convergence error. Rounding errors can be minimized by double-precision calculations. Discretization error can be qualitatively evaluated by grid convergence study. Convergence error can be minimized by calculating until the solution converges sufficiently.
5. Evaluate total uncertainty by integrating input uncertainty, model form uncertainty, and numerical approximation. The uncertainty of the objective variables is obtained from the 95% confidence interval of total uncertainty.

In this paper, the wind velocity in the test section is set as the objective variable. The 1st, 2nd, and 3rd bends, the straightening screen, the characteristic curve of the fan, and the drag of the generic aircraft model are identified as the sources of uncertainty. Sensitivity analysis for the numerical model showed that the 1st bend and the characteristic curve of the fan have a significant effect on the wind velocity. Thus the probabilistic distribution of parameters for the 1st bend and the characteristic curve is determined by measurements (111 points), and these two variables were classified as aleatory uncertainty. Measurements of the 2nd and 3rd bend and straightening screen are limited (only 3 points) and the drag is also limited (4 points) so these four variables were classified as epistemic uncertainty because measurements are too few to determine their probabilistic distributions. The drag of the generic aircraft model was measured with an angle of attack of 0 degrees. 125 points are samples from four epistemic uncertainties by LHS, and 20 points are samples from two aleatory uncertainty by the MC method. A total of 1 million samples were generated. The rotational speed was fixed at 181 rpm. 1 million times computation of the numerical model was performed, and the probabilistic distribution of the wind velocity was obtained. Figure 2 shows the Cumulative Density Function (CDF) of the wind velocity. In every single CDF, epistemic uncertainties are fixed, and aleatory uncertainties are propagated through the model. The enclosed area by the CDFs is called the p-box (probability box). The advantage of the p-box is to simultaneously evaluate both the epistemic and aleatory uncertainties having bias and random components, respectively. It is found from Fig. 2 that the input uncertainty of the wind velocity is 57.96 ~ 58.49 m/s from the 95% confidence interval in the present numerical model.

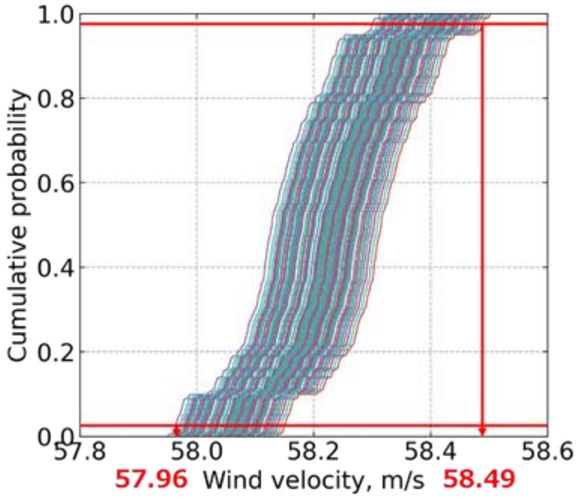

Figure 2. Input uncertainty of the predicted wind velocity in p-box form. Colors indicate every single CDF.

To evaluate the model form uncertainty, the experimental measurements and numerical prediction of the wind velocity are compared. The wind velocity was measured four times in this study. Instead of the model form uncertainty proposed by Roy and Oberkampf (2011), the modified area validation metric (Voyles & Roy, 2015) was used to avoid over-estimation of model form uncertainty and consider the number and confidence interval of measurements. In Fig.3, the blue dotted lines show the CDF of the measurements, the red dotted line shows the input uncertainty of the numerical model, and the solid lines in each color show the 95% confidence interval of each CDF. The hatched area (yellow, pink, with overlapping parts in orange) represents the model form uncertainty, which are $d^{+}_{0.95} = 1.73\ \mathrm{m/s}$ and $d^{-}_{0.95} = 1.83\ \mathrm{m/s}$.

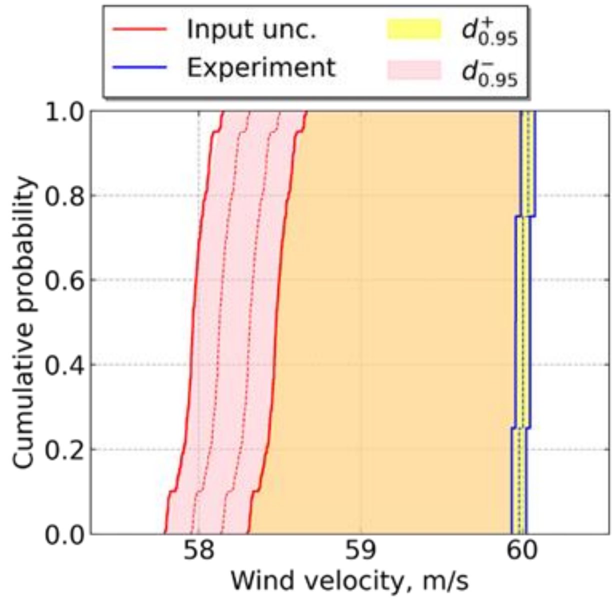

Figure 3. Model from the uncertainty of the predicted wind velocity.

Regarding numerical approximation, the diffuser is modeled empirically (Idelchick, 1996) so that there is no discretization error. On the other hand, differential equations are solved for the straight duct model where discretization error may occur. The straight duct model was divided into 1, 2, and 4 segments, and the convergence of the result was examined. It was found that the discretization error was less than 0.01% which was negligible. Moreover, the present software uses a double-precision floating point, so the rounding error is negligible. Therefore, the numerical approximation is negligible in this numerical model.

Figure 4 shows the total uncertainty of the wind velocity obtained by integrating the input uncertainty and the model form uncertainty. The p-box of the total uncertainty is obtained by moving the lower and upper bound of the input uncertainty by model form uncertainty of $d^{+}_{0.95}$ and $d^{-}_{0.95}$, respectively as shown in Fig. 4. It is found that the 95% confidence interval of the wind velocity is 56.13 ~ 60.21 m/s.

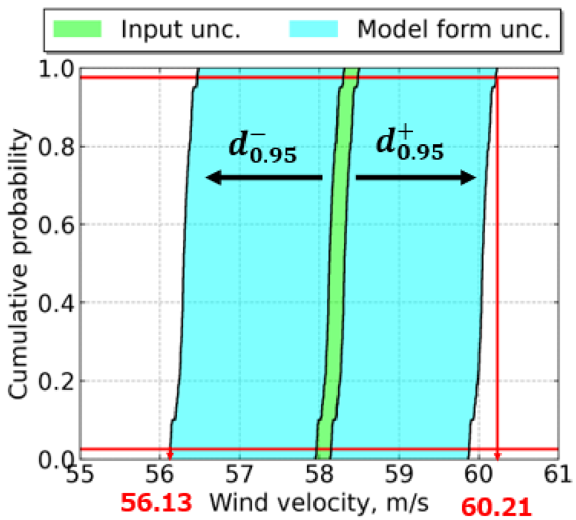

Figure 4. The total uncertainty of the predicted wind velocity.

5. Demonstration of Anomaly Detection

A demonstration of real-time anomaly detection was conducted. Anomaly detection is possible by defining the normal space from the training dataset including both normal and anomaly conditions in general. Since the test model changes depending on users in the wind tunnel test, there is no training dataset to determine the normal space. Therefore, the result of UQ is used to define the normal space.

Figure 5 shows the results of the demonstration. The red line shows the measured wind velocity. As described in Section 2, leakage of the total pressure tube in the pitot velocimetry was injected. Since the opening ratio of the need valve was opened at 78 s and 143 s, the measured wind velocity was decreased. The blue line shows the predicted wind velocity by the numerical model in real time. The green area represents the normal space (56.13 ~ 60.21 m/s) determined by the UQ result. There was no leakage from 0 s to 78 s, and the measured wind velocity remains within the normal space. This shows that the present method successfully detected the normal condition. At 79 s, the wind velocity drops from 60 m/s to 56.2 m/s. This is the anomaly of underestimation of the wind velocity because of the valve opening. The measured wind velocity remains within the normal space, which indicates that the anomaly state was not detected. At 143 s, the wind speed drops again from 56.2 m/s to 52.5 m/s by increasing the valve opening. The measured wind velocity deviates from the normal state, and the present method could detect the anomaly. From this demonstration, it is found that anomaly detection can be performed by using the UQ result of the model-based numerical model. To increase the accuracy of anomaly detection, it is necessary to determine the normal space more accurately, i.e., reduce the uncertainty of the numerical model through Uncertainty Management (UM) (Pecht&Kang, 2018) which is the attempt to reduce the uncertainty of numerical models. Sensitivity analysis is conducted in UM to clearify the influence of explanatory variables (model parameters) on objective variables (uncertainty of the numerical model). Reducing the uncertainty of most influential explanatory variables will effectively reduce the uncertainty of objective variables. To reduce the uncertainty of the most influential explanatory variables, additional measuremens are conducted to determine or improve the probability distribution.

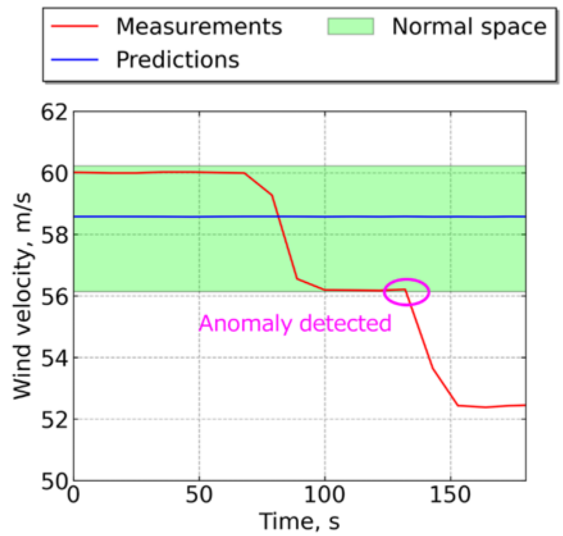

Figure 5. Result of the demonstration of real-time anomaly detection with the normal space determined by UQ.

6. Conclusion

To develop autonomous technology for spacecraft, this study demonstrates real-time anomaly detection in the 6.5m × 5.5m wind tunnel in Japan Aerospace Exploration Agency (JAXA), called LWT1. To overcome the difficulty of insufficient training data including both normal and anomaly conditions, this study developed a numerical model, and the Uncertainty Quantification (UQ) consisting of input uncertainty, model form uncertainty, and numerical approximation was conducted to define the confidence interval of the numerical result. It was found that the 95% confidence interval of the wind velocity in the test section was 56.13 ~ 60.21 m/s, which was used to define the normal space. In this study, the present method was demonstrated by injecting a synthetic anomaly caused by flow leakage in the pitot velocimetry. It was found that real-time anomaly detection was possible when the leakage flow was large. To increase the accuracy of anomaly detection, Uncertainty Management (UM) is needed to reduce the uncertainty.

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