PHM for Spacecraft Propulsion Systems: Developing Resilient Models for Real-World Challenges

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ABSTRACT

This paper extends the research presented at the Prognostics and Health Management (PHM) Asia-Pacific 2023 Conference Data Challenge, focusing on a more pragmatic approach to spacecraft propulsion system health assessment. While the previous competition saw a variety of solutions, they predominantly relied on the assumption of highly stable initial hydraulic conditions – an idealization seldom met in real-world scenarios. In practical settings, factors such as operational noise, recent operational states, and ambient environmental conditions significantly disrupt this stability, rendering such solutions less feasible. Addressing this gap, our current study introduces a novel diagnostic model capable of valve faults without depending on the initial stable state of hydraulics. This approach marks a significant shift from our previous methodology, which primarily utilized similarity measures and physics-inspired features to classify health states and identify solenoid valve faults in spacecraft propulsion systems. The proposed model in this paper is validated against a diverse set of conditions, emphasizing its robustness and applicability in fluctuating real-world scenarios. Our findings demonstrate that the new model not only effectively diagnoses system health under varied and less controlled conditions but also enhances the practicality of spacecraft health management, offering a more adaptable solution in the face of operational uncertainties.

1. INTRODUCTION

Propulsion systems in spacecraft are essential for navigating through the cosmos, and their dependable and effective operation is critical. Therefore, the health management of these systems is of utmost significance. The role of Prognostics and Health Management (PHM) is central in ensuring this dependability, as it allows for the early identification and assessment of potential problems or irregularities within the propulsion mechanisms.

To promote Spacecraft PHM, the Japan Aerospace Exploration Agency (JAXA) created and released a dataset to the public (Tominaga et al., 2023), and at the same time, a data challenge was held at the PHM Asia Pacific 24 conference to facilitate the use of this data (PHMAP 2023 Secretariat, 2023). The Data Challenge required complex diagnostics such as analytical detection, classification, and regression, and many institutions took on the challenge. Despite the complexity of the problem, the top three teams of the data challenge ultimately succeeded in creating highly accurate models, and these results have been compiled and published in papers (Kato, et al., 2023) (Lee et al., 2023) (Minami & Lee, 2023). This effort was an important step in the promotion of spacecraft PHM. However, there are two major problems in adapting these models to the real world.

The first problem is the presence of non-noise regions that are unique to this data set. All of the top three teams found and used a time region in the given pressure sensor data that is completely free of noise. In this time region, all data sets with identical health conditions have the same pressure values, and the differences among Spacecraft individuals and data are zero. Specifically, the given pressure time series data is completely free of noise/variation in the initial 0.1 seconds (0 to 0.1 sec) of the 1.2 seconds. This is evidenced by the results of the data analysis (Kato, et al., 2023). This is presumably because this data set was generated by simulation. Since this specificity is considered to be different from the behavior of pressure in the real world, there is a concern that even if a high-performance model is created using only the completely noise-free portion of this data set, it will be completely useless in the real world if any noise is added, or if there is any variation in the data. To dispel this concern, it is necessary to evaluate the model using data with noise/variance.

The second problem is the use of valve open-state data. The data given are data from three iterations of valve opening and closing, and the three proposed models use only the data from that first valve open state. However, in the valve open state, the propulsion system is not closed as a system and its pressure behavior is subject to external influences. Therefore, the pressure in the valve open state is a very complex and unpredictable behavior. Therefore, in pursuit of a robust model, state estimation is required using the pressure in the valve closed state, i.e., when the system is closed.

Because of these two major problems, the models proposed in the data challenge may not stand up to use in the real world.

To summarize the above points:

Firstly, regarding the variance-free region of the dataset:

- The spacecraft valve dataset contains an unrealistic time region that is free of variance.
- The models proposed in the data challenge use this variance-free time region, which may result in poor performance when applied to real-world data.
- To ensure the proposed models perform well in the real world, it is necessary to validate them using time regions with variance.

Next, regarding the data during valve opening and closing:

- When the valve is open, the system is open, making the sensor data complex and unpredictable. This cannot be verified until tested with real-world data.
- For building a robust model, it is preferable to use data from the closed system when the valve is closed.
- All models proposed in the data challenge are designed and trained using data from the valve-open state.
- To construct a robust model, it is necessary to design new models based on data from the valve-closed state.

To address this issue, this paper examines and evaluates the models for the PHM of spacecraft valve under the restriction that data from the variance-free portion is not used and assumes following two cases: Case 1 uses data from the valve open state, while Case 2 uses data from the valve closed state.

Model construction was examined under these scenarios to promote the construction of a more robust PHM model.

2. Problem Statement

The PHM Asia-Pacific 2023 Conference Data Challenge focused on Prognostics and Health Management for spacecraft propulsion systems, with the system's schematic illustrated in Figure 1. The training dataset provides 177 sets of synthetic data produced by simulations. Each set includes measurements from seven pressure sensors labeled P1 to P7, as depicted in Figure 1. These measurements were taken at a sampling rate of 1 kHz, throughout 1200 ms, and encompass three cycles of valve open-close operations, as shown in Figure 2.

The training dataset covers three distinct spacecraft, labeled #1 through #3, and it encompasses three different health conditions: normal operation, bubble anomalies, and solenoid valve faults. Solenoid valve faults could potentially occur in one of the four valves labeled SV1 through SV4, as shown in Figure 1. In the event of a fault, the solenoid valves may open anywhere from 0% to 100% of their full range. Under normal conditions, they open 100%. Note that the training data only include cases in which the valve open ratios are 0%, 25%, 50%, 75%, and 100%. The competition aims to utilize the 177 training data points to evaluate the health conditions of the 46 test data points. Half of the test data originates from spacecraft #4, which is not represented in the training set.

In this study, we focus only on the most complex task of estimating valve apertures. Two problem settings, Case 1 and Case 2, are used to validate the model for the two major problems described in the Introduction. Each is described in detail in the following sections.

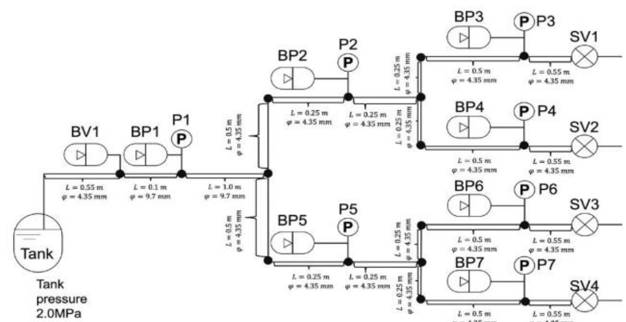

Figure 1. Schematic of experimental propulsion system

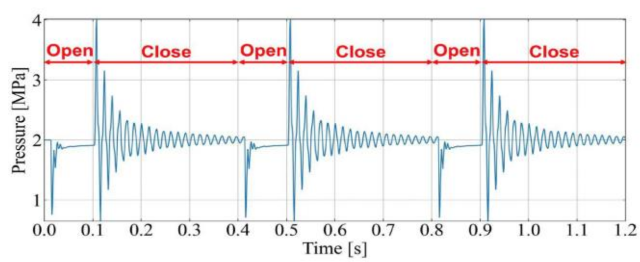

Figure 2. Typical pressure profile

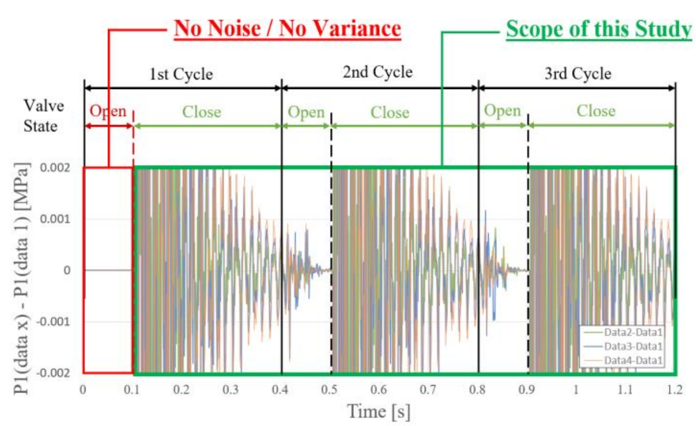

Figure 3. Pressure differences among normal data

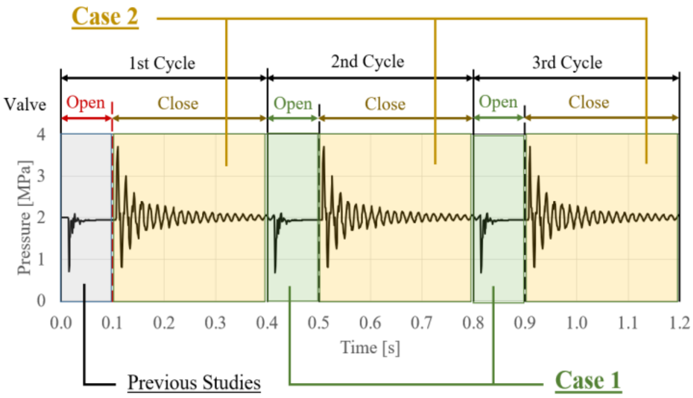

Figure 4. Data Regime

2.1. Case 1: Valve opening ratio prediction using data at valve opening with noise/variance

In Case 1, only the data of the valve open state of the second and third cycle of the valve open/close cycles is used. Specifically, as shown in the green area of Figure 4, out of the total 1.2 seconds of pressure data, only 0.4 to 0.5 seconds and 0.8 to 0.9 seconds, for a total of 0.2 seconds of data are used.

Case 1 evaluates model performance with the following metrics as well as data challenge

The evaluation metric is as follows:

$$Total\ Score = \frac{\sum_{i}^{Ntest} Score_i}{\sum_{i}^{Ntest} Score(max)_i} \quad (1)$$

Here, N_{test} is the number of test data. $Score_i$ is as follow:

$Score_i$: For the solenoid valve correctly identified as fault, prediction of the opening ratio: max (20-|truth – prediction|, 0)

For spacecraft #4, $Score_i$ are doubled, considering the difficulty. $Score(max)$ is the score if there were no prediction errors. Therefore, the total score can range from 0% to 100%.

2.2. Case 2: Valve opening ratio prediction using data at valve closed

In Case 2, only the data of the valve closed state for the 1st, 2nd, and 3rd cycles of the whole sensor data are used. Specifically, as shown in the orange area of Figure 4, out of a total of 1.2 seconds of pressure data, 0.1 to 0.4, 0.5 to 0.8, and 0.9 to 1.2 seconds of pressure data are used.

Since Case 2 is more difficult than Case 1 and it is difficult to estimate the valve opening ratio with continuous values, set the classes according to the valve opening ratio as shown in Figure 5, and set the problem as a classification problem to predict the valve opening ratio class instead of a regression problem to predict the numerical value of the valve opening ratio.

The classification models are evaluated using the following metric where TP is the total number of test data that are correctly classified.

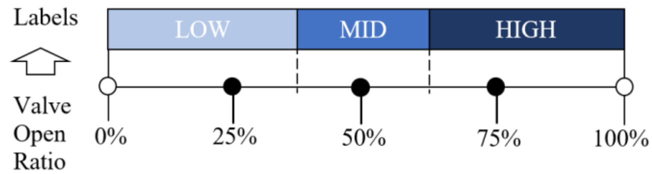

Figure 5. Labeling of valve opening ratio

$$Classification\ Accuracy = \frac{TP}{N_{test}} \quad (2)$$

3. Background: Model Selection

PHM often face the challenge of dealing with noise and variability in data, which can obscure the fundamental patterns necessary for accurate diagnosis and prediction. A common approach to address this issue is the use of filtering techniques, such as moving averages and other signal processing methods.

Simple filtering techniques, such as moving averages and other basic smoothing methods, are widely used in PHM to reduce noise and improve signal quality. For instance, Mubarak et al. (2023) demonstrated that applying a moving average filter to time series signals outperformed traditional condition monitoring methods in tasks such as Rolling Element Bearing Fault Diagnosis and Hydraulic Accumulator State Classification. Similarly, Boškoski and Urevc (2011) showed that passing vibration signals through a band-pass filter effectively removed noise, enhancing the accuracy of bearing fault detection by analyzing the envelope spectrum of the filtered signals.

However, these simple methods have significant limitations. The primary concern is their inability to distinguish between noise and useful information. As a result, essential diagnostic information may be inadvertently removed along with the noise. This is particularly problematic in scenarios like predicting valve opening degrees, where minute pressure fluctuations carry significant diagnostic value. Standard noise removal techniques are likely inappropriate here, as they can degrade model performance by losing critical diagnostic information.

To address the limitations of simple filtering, advanced techniques such as deep learning are utilized (Najafabadi et al., 2015). Deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs), excel in distinguishing noise from useful signals. For example, Baptista and Henriques (2022) used a onedimensional denoising GAN (1D-DGAN) to filter noise from turbofan engine operational data, significantly improving fault detection accuracy. Liu et al. (2018) proposed a novel bearing fault diagnosis method using an autoencoder in the form of an RNN. This method employed a Gated Recurrent Unit (GRU)-based denoising autoencoder to predict multiple vibration values of rolling bearings for the next period from the previous period. The proposed method demonstrated satisfactory performance with high robustness and classification accuracy.

While these advanced methods are effective in removing noise without losing useful information, they typically require large amounts of training data. Such extensive datasets are essential for the model to learn complex patterns and distinguish subtle differences between noise and useful signals.

In contrast, the dataset used in this study is very limited. This limitation makes the application of deep learning approaches impractical, as the model is likely to overfit the small dataset and fail to generalize to unseen data.

Given these constraints, rule-based models or simple models with fewer parameters are more suitable for this study. Therefore, this study focuses on designing and validating methods for the two cases set in the previous section, based on models proposed in the data challenge that meet these criteria. Specifically, we use the polynomial regression model based on pressure drop proposed by Minami and Lee (2023) and the similarity-based regression model proposed by Kato et al. (2023).

In Case 1, we directly utilize the existing models proposed in the data challenge to evaluate their performance in the presence of noise and variability. The primary focus is to assess whether and to what extent the performance of the previously proposed models degrades with increased variability.

In Case 2, since the models proposed in the data challenge are based on the assumption of valve open states, they cannot be used directly. This study examines the adaptation of these models' features to valve closed states. By doing so, it becomes possible to leverage the existing model structures while adapting them to new conditions.

4. METHODOLOGY AND RESULTS

In this section, the design and validation of models for two distinct cases are conducted. For both cases, a linear regression model is adopted as the benchmark method. This benchmarking methodology involves extracting nine types of basic statistics (Mean, Standard Deviation, Minimum, 25th Percentile, Median, 75th Percentile, Maximum, Skewness, Kurtosis) from each of the seven sensors. After extraction, dimensionality reduction is performed using PCA.

4.1. Case 1

In Case 1, the green area in Figure 4. Here, we examine how well the solution proposed in the data challenge maintains performance in a noisy and varied environment.

4.1.1. Methodology

As shown in Figure 1, there were two main valve opening prediction models implemented in the data challenge: one is the method that estimates the valve opening ratio by performing a polynomial fit based on the pressure drop/slope immediately after valve opening (Lee et al., 2023) (Minami & Lee, 2023). The other is the method that uses the similarity of the overall pressure during the first 0.1 seconds after the valve opens to estimate the pressure. (Kato, et al., 2023).

To adapt these proposed methods for Case 1, here, the predicted valve open ratio is calculated for each of the predictions for the 2^{nd} cycle data (0.4 to 0.5 sec) and the 3^{rd} cycle data (0.8 to 0.9 sec), and take the average of these is the final predicted value

4.1.2. Results

The prediction results from each model are shown in Table 1, and the calculation results of the estimation accuracy are shown in Figure 6.

Polynomial Fit's model is still able to maintain a high accuracy rate of 96%, albeit with lower accuracy, relative to previous results in the noiseless region. This suggests that the pressure drop is an important indicator that is not easily affected by noise. On the other hand, the model using Similarity shows a significant drop in accuracy, from 89% to 48%. This indicates that Similarity is susceptible to noise and has poor generalization performance when the valve is open. These results indicate that the Polynomial Fit method, which focuses on the initial pressure drop, is effective in estimating the valve opening ratio, even with noise and variation, as long as data on the valve opening state is available. On the other hand, since the data is a simulation and the number of N is small, it is necessary to verify the validity of this finding by measuring data in a setting closer to reality.

Table 1. Models and predicted valve opening ratio

Spacecraft	Case	Valve	Open Ratio [%]						
			Ground Truth	Estimation					
				Benchmark		①Polynomial		②Similarity	
				1st Cycle	2nd, 3rd Cycle	1st Cycle	2nd, 3rd Cycle	1st Cycle	2nd, 3rd Cycle
1	179	2	22	25	**40**	22	**22**	24	**24**
1	181	4	76	87	**72**	76	**71**	77	**79**
1	188	1	5	0	**0**	5	**4**	20	**19**
1	190	3	46	25	**42**	46	**46**	46	**42**
1	199	1	98	95	**100**	98	**99**	97	**96**
4	202	3	44	28	**41**	44	**44**	44	**42**
4	205	2	94	94	**90**	94	**95**	95	**37**
4	211	1	95	93	**95**	95	**95**	93	**62**
4	212	2	70	78	**82**	70	**71**	67	**16**
4	214	4	24	28	**20**	24	**25**	25	**21**

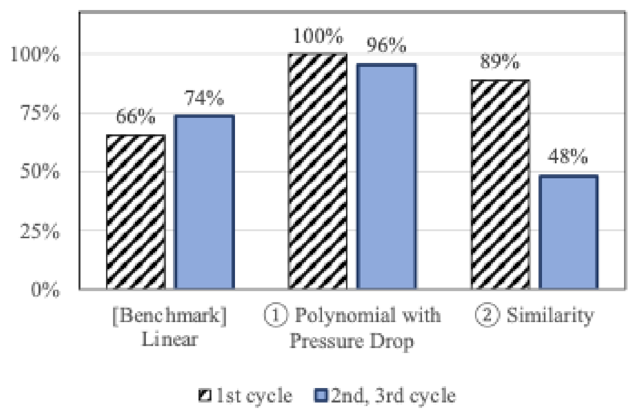

Figure 6. Regression accuracy

4.2. Case 2

In Case 2, only the data in the orange region of Figure 4 is used as a more practical but more difficult setting compared to Case 1.

4.2.1. Methodology

Unlike Case 1, the solution proposed in the data challenge cannot be used, thus a new model must be devised. Theoretically, the difference in pressure behavior with valve opening is determined only by the pressure state immediately before closing the valve, and it all returns to a constant pressure with time after closing. In other words, the difference in valve opening ratio has the greatest effect on the pressure immediately after the valve is closed, and as time passes, the difference in valve opening ratio has less effect on the pressure difference. Therefore, we devised the following two models that focus on the pressure behavior immediately after the valve is closed.

4.2.2. Method 1: Valve closing pressure surge

The first proposed model focuses on the pressure increase immediately after valve closing, similar to the focus on pressure drop in Case 1. As an example, shown in Figure 7, the pressure rise after valve closing is divided by the valve opening %, which may be used to classify the pressure rise. The label of the training data with the closest pressure based on the pressure after the specified time after the valve is closed is estimated as the label of the test data. Three models are created based on the pressure at 106 ms, 107 ms, and 108 ms after the valve was closed.

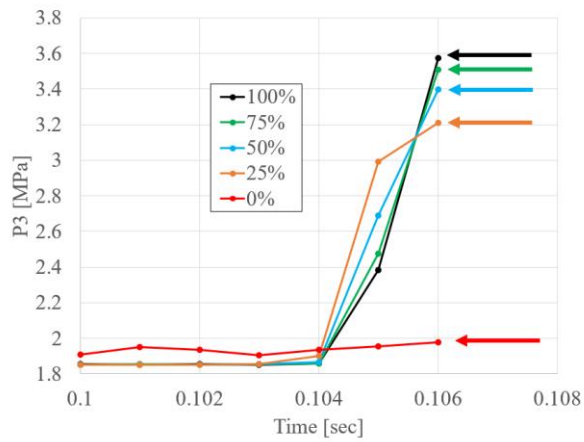

Figure 7. Example of pressure surge after valve closed (SV1)

$$\mathit{Predicted\ Label} = \mathit{Label}\left(\underset{i}{\operatorname{argmin}} \| P(train_i) - P(test) \| \right) \quad (3)$$

where training is the with training data, P is the pressure at the valve fault location, Label is the label of the training data, and Predicted Label is the label of the test data.

4.2.3. Method 2: Similarity

In this proposed model, as shown in Figure 8, the Euclidean distance is measured as the similarity of waveforms during a certain number of seconds after the start of valve closing operation, and the training data label with the highest similarity is used as the prediction label. Three models were created based on waveforms of different lengths (100 ms, 10 ms, and 5 ms).

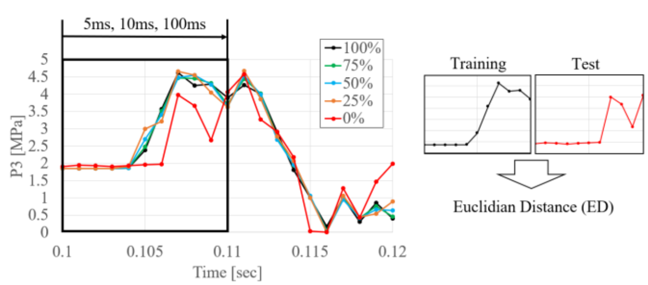

Figure 8. Similarity measurement process

$$\begin{aligned} &Predicted\ Label \\ &= Label\ (\underset{i}{\operatorname{argmin}}(\ ED(train_i, test))) \end{aligned} \quad (4)$$

$ED(train_i, test)$ calculates the Euclidian distance of i-th training data and test data as a similarity.

4.3. Results

Table 2, Figure 9, and Figure 10 show the classification results and the results of valve opening estimation for the two models.

Table 2. Classification Results

Spacecraft	Case	Valve	Open Ratio [%] Ground Truth	Estimation Bench mark	①Polynomial 106 ms	①Polynomial 107 ms	①Polynomial 108 ms	②Similarity 100 ms	②Similarity 10 ms	②Similarity 5 ms
1	179	2	Low	Mid	Low	Low	Low	Low	Low	Low
1	181	4	High	High	Mid	High	High	High	High	High
1	188	1	Low	Low	Low	Low	Mid	Low	Low	Low
1	190	3	Mid	Mid	Mid	High	Mid	Mid	Mid	Mid
1	199	1	High	High	High	Mid	High	High	High	High
4	202	3	Mid	Mid	Mid	Mid	Low	High	Mid	Low
4	205	2	High	High	Low	High	Low	High	High	High
4	211	1	High	High	High	Low	Low	High	High	High
4	212	2	High	High	Low	High	Low	High	High	High
4	214	4	Low	Low	Low	Low	Low	High	Low	Low
No. of Correct Answer				9	7	7	5	8	10	9

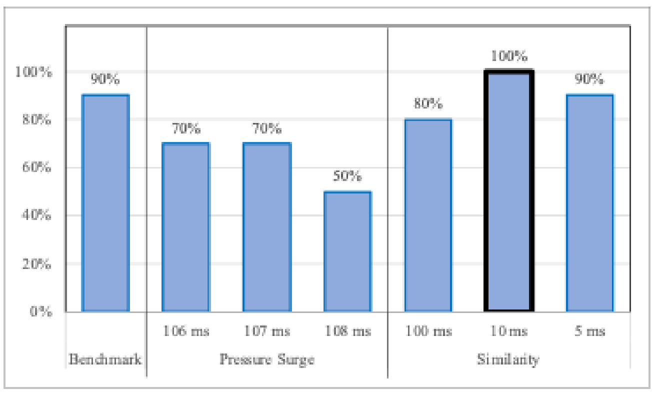

Figure 9. Classification Accuracy

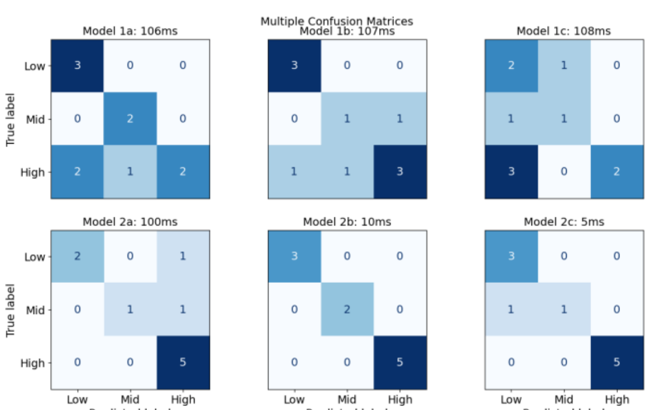

Figure 10. Confusion Matrix

The results show that Method 2 has better overall accuracy than Method 1 and the benchmarking method. The results of Method 1 show that in Case 1, high accuracy can be obtained only with pressure drop, while in Case 2, accuracy is not as good as it was, only with pressure rise. Possible reasons for this include variations in the timing of valve switching and the fact that the pressure rise is more complex than the pressure drop because it is caused by pressure propagation throughout the system.

Among the Method 2, the best accuracy was found when 10 ms waveforms were used. This suggests that there may be information useful for valve opening prediction in a specific interval. Although it is difficult to conduct a detailed analysis here due to the small amount of data, if more data were available, it would be possible to conduct an EDA and analyze the useful data areas.

From the above analysis, it is found that it is possible to use similarity to classify valve opening ratio classes and estimate intervals using only data for the closed valve state.

5. Conclusions

To construct a practical and robust spacecraft PHM model, we built and validated a valve opening prediction model with the constraint of eliminating noise/variation-free regions from the data set.

In Case 1, we verified the capability of the model proposed in the data challenge based on the valve opening data. The results showed that the regression model focusing on pressure drop had a regression accuracy of 96% even in the presence of noise and variability. On the other hand, the model using similarity was found to be only 48% accurate. This shows that the pressure drop model can produce robust results even with noise.

In Case 2, the model is built using only data from a closed system and closed valves. The model focusing on the pressure increase achieved only 70% accuracy in classification, while the model focusing on similarity achieved 100% accuracy. Further development of the model is needed to realize point estimation by regression rather than interval estimation of valve opening ratio by classification.

6. Further Research

In this study, considering that system behavior generally becomes unstable when the system is open, a method that does not use the valve-open data from the dataset was proposed in Case 2. However, since the extent of instability depends on the application and the usage environment, it is necessary to collect data through experiments and verify the validity in future work.

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