# PHM for Spacecraft Propulsion Systems: Similarity-Based Model and Physics-Inspired Features

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## Abstract

This paper presents a methodology designed for the Prognostics and Health Management (PHM) Asia-Pacific 2023 Conference Data Challenge. In particular, this study targets the health assessment of spacecraft propulsion systems. The challenge involved analyzing and categorizing a simulation-generated dataset that included four unique spacecraft and multiple health conditions, such as normal operation, bubble anomalies, and solenoid valve faults in various system locations. The proposed approach uses a two-step process. First, a model based on similarity measures is employed to classify the data into one of four health states. Then, a model incorporating physics-inspired features is utilized in solenoid valve faults to identify the fault location and estimate the valve opening ratio. The validity of the model is confirmed through cross-validation with the training dataset, which achieved a flawless total score across all permutations. Our method effectively categorizes the test data, including cases from a spacecraft not covered in the training, thereby securing a top position in the competition. The findings highlight the strength of our proposed model, which uses physics-inspired features to predict valve opening ratios, proving useful in managing and interpreting complex, unfamiliar spacecraft health data.

## 1. Introduction

Spacecraft propulsion systems serve as the fundamental mechanism that facilitates the navigation of spacecraft through space. Their reliable and efficient functioning is of paramount importance, making their health management a crucial aspect. Prognostics and Health Management (PHM) play a pivotal role in maintaining this reliability by enabling the early detection and diagnosis of potential issues or anomalies in propulsion systems.



The main tasks involved in PHM typically include anomaly detection, classification, and regression (Lee et al.,2014) (Tsui et al., 2015). Anomaly detection aims to identify departures from normal operations, which may signal potential unanticipated system failures or faults. Classification is employed to diagnose known faults, differentiating them from normal operational states and other types of known faults. Conversely, regression is used to gauge the extent or severity of a given fault, providing a quantitative measurement of the impact of the fault on the system's operation.

A similarity-based method is often adopted for PHM tasks (Wang et al., 2008) (Duan et al., 2021). This method operates based on the principle of comparing the current system state to a library of known states or fault patterns. A similarity-based anomaly detection method recognizes deviations from normal operation by juxtaposing real-time data with baseline or normal operational data. The more significant the deviation, the higher the likelihood of an anomaly. For instance, Chang et al. (2014) present a similarity-based method to expedite the qualification process of LEDs. This method analyses and clusters LED spectral data to identify the early indicators of degradation. Hendrickx et al. (2020) enhance a fleet-based industrial asset monitoring framework by refining the anomaly scoring system with machine similarities within the fleet, permitting more precise, continuous, and individualized scoring that accurately pinpoints machine anomalies.

In classification tasks, the same concept is utilized; However, the current state is compared to multiple known fault conditions. The system condition or fault that most closely aligns with the current state is then determined as the probable state of the system. For example, Senanayaka et al. (2022) propose an innovative method of classification for machine state prediction using time-series signals in predictive maintenance, termed similarity-based multi-source transfer learning. The model is validated using datasets gathered from various rotating machinery, showing superior performance over conventional methods. The effectiveness of the similarity-based method depends on the quality and thoroughness of the comparison library, underscoring the necessity for a diverse and well-represented dataset of system conditions and fault patterns.

Data-driven models typically form the foundation of PHM tasks. When constructing such models, incorporating domain-specific knowledge, such as the physical laws that dictate a system's behavior, can prove advantageous. This is often accomplished through the meticulous design of the model's features (Ompusunggu and Hostens, 2021). These physics-informed features often enhance the performance and interpretability of the model, particularly when the available data are sparse or noisy.

In this study, we outline the development of a data-driven model to assess the health conditions of spacecraft propulsion systems for the PHM Asia-Pacific 2023 Conference Data Challenge.

## 2. Problem Statement

The PHM Asia-Pacific 2023 Conference Data Challenge focuses on Prognostics and Health Management (PHM) 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, over a duration of 1200 ms, and encompass three cycles of valve open-close operations, as shown in Figure 2.

The dataset covers three distinct spacecrafts, labeled #1 through #3, and it encompasses three different health conditions: normal operation, bubble anomalies, and solenoid valve faults. Bubble anomalies could potentially occur in one of the eight locations, indicated as BV1 and BP1 through BP7, as shown in Figure 1. Similarly, 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 aim of the competition is to utilize the 177 training data points to evaluate the health conditions of the 46 test data points. It should be noted that the test set includes an unknown anomaly mode not present in the training set, and participants should remain cognizant of this possibility. If a bubble anomaly is detected, its location must be specified. Similarly, in case a solenoid valve fault is identified, both the location of the fault and the degree to which the valve is open should be indicated. Half of the test data originates from spacecraft #4, which is not represented in the training set.

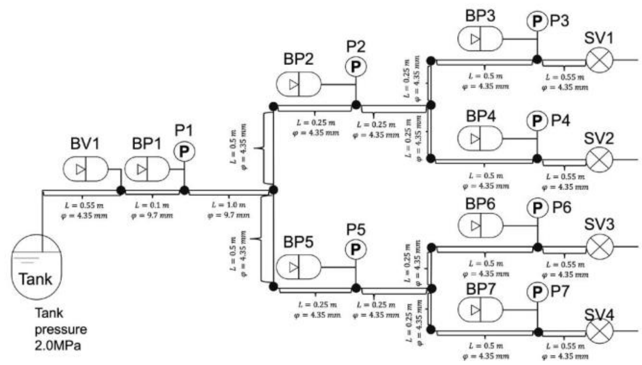


Figure 1 Schematic of experimental propulsion system

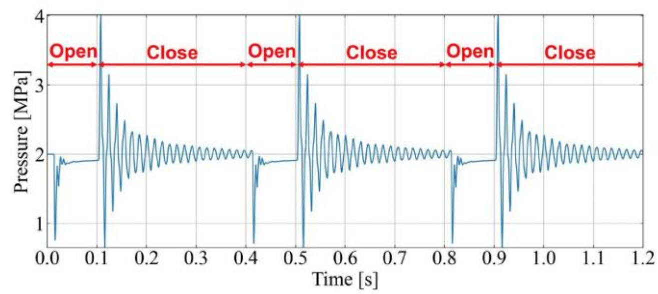


Figure 2 Typical pressure profile

The evaluation metric is as follows:

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

$$Score_i = T1_i + T2_i + T3_i + T4_i + T5_i \tag{2}$$

Here, $N_{test}$ is the number of test data. $T1_i$ to $T5_i$ are as follows:

$T1_i$: Classification of normal/abnormal condition (10 points)

$T2_i$ : For the data correctly detected as abnormal, classification of bubble contamination anomaly/solenoid valve fault/ unknown fault (10 points)

$T3_i$ : For the data correctly identified as bubble contamination, identification of bubble location (10 points)

$T4_i$: For the data correctly identified as solenoid valve fault, identification of the failed valve: (10 points)

$T5_i$: For the solenoid valve correctly identified as fault, prediction of the opening ratio: max (20-|truth – prediction|, 0)

For spacecraft #4, $T1_i$ to $T5_i$ 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%.

## 3. METHODOLOGY

### 3.1. Overview

Figure 3 illustrates the flowchart of the methodology we utilized in this data challenge. Health assessment is conducted in two primary steps. Initially, the data is categorized into one of the four health conditions across all the datasets. For bubble anomalies, we also determine their locations, leading to the classification of data into 11 distinct categories. This is achieved using a similarity-based model constructed on the extracted data. Subsequently, the data identified as being affected by a solenoid valve fault undergoes a detailed diagnosis. The fault location is determined by leveraging the extracted features, and the valve open ratio is estimated. The specifics of each process are described in detail in the following sections.

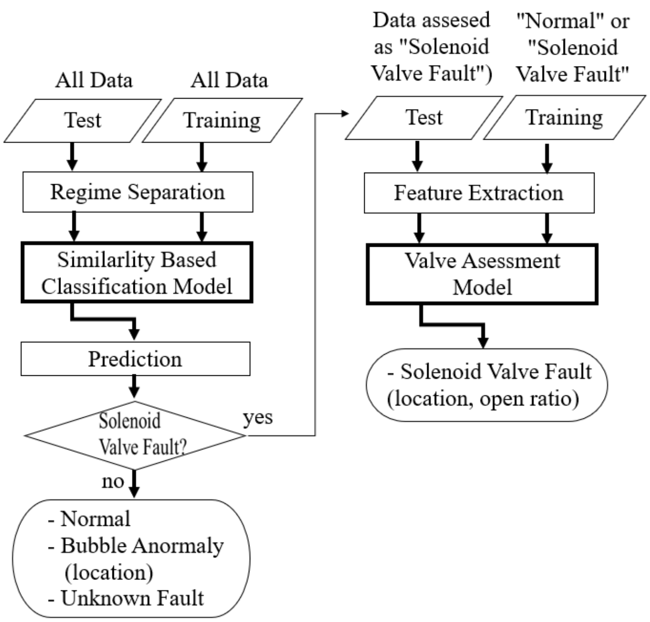


Figure 3 Methodology Overview

### 3.2. Regime Separation

Portions of the sensor data relevant for classification are isolated. Although the data encompasses three cycles of the valve opening and closing, only the information from the initial valve opening is extracted. In other words, out of the total 1.2 seconds of data, only the first 0.1 seconds is employed in the classification model. This approach is taken because, unlike in the second and third cycles, the hydraulic pressure in the first cycle remains consistent at the initial state of 0 seconds, eliminating any variation in hydraulic pressure behavior due to individual or sample differences.

To quantify this variability, an analysis of the training dataset is performed using Dynamic Time Warping (DTW). DTW is a distance-based method that measures the similarity between two time-series data sets (Berndt & Clifford, 1994). By aligning the time axes of the data, DTW permits non-linear time warping, thereby facilitating the discovery of an optimal matching path and the computation of distance. This mechanism enables an effective comparison of time-series data.

The means and variances of the in-class DTW distance *d* are calculated for each health condition using the following equations:

$$d_{i,j} = \left(DTW\left(X_{i,j}, \bar{X}_j\ \right)\right), \quad \bar{X}_j = \sum_i X_{i,j} \qquad (3), (4)$$

Here, $X_{i,j}$ represents the *i*-th training sample with *j*-th health condition.

Table 1 presents the calculation results of mean and standard deviations of $d_{i,j}$. These findings demonstrate that there is no bias or variation between samples within the same health condition during the first 0.1 seconds. This also applies to the solenoid valve fault conditions. Consequently, this segment of data can be utilized to achieve robust estimation.

Table 1 In-class DTW distance (mean ± std.)

| Conditions | 0.0 – 0.1 sec | 0.1 – 0.4 sec | 0.4 – 0.5 sec | 0.5 – 0.8 sec | 0.8 – 0.9 sec | 0.9 – 1.2 sec |
|---|---|---|---|---|---|---|
| Normal | 0.0±0.0 | 174.1±61.4 | 10.2±3.4 | 174.8±61.2 | 10.6±3.6 | 175.6±63.5 |
| Bubble: BP1 | 0.0±0.0 | 168.5±28.0 | 10.6±1.4 | 167.3±28.3 | 10.8±1.2 | 166.5±27.0 |
| Bubble: BP2 | 0.0±0.0 | 134.5±24.5 | 5.4±1.1 | 135.7±13.2 | 4.7±0.9 | 137.7±13.3 |
| Bubble: BP3 | 0.0±0.0 | 140.6±14.9 | 4.8±0.6 | 137.0±14.0 | 3.7±0.3 | 131.6±10.9 |
| Bubble: BP4 | 0.0±0.0 | 142.1±38.1 | 6.3±2.0 | 140.6±30.4 | 7.3±2.4 | 145.5±36.7 |
| Bubble: BP5 | 0.0±0.0 | 165.0±39.0 | 14.1±1.7 | 161.9±34.5 | 11.2±1.1 | 163.0±34.4 |
| Bubble: BP6 | 0.0±0.0 | 119.7±31.6 | 3.2±0.8 | 121.4±31.9 | 3.0±0.4 | 121.2±32.0 |
| Bubble: BP7 | 0.0±0.0 | 135.5±25.9 | 2.4±0.5 | 152.2±36.0 | 6.8±1.7 | 151.8±34.3 |
| Bubble: BV1 | 0.0±0.0 | 180.9±23.2 | 10.4±1.4 | 187.8±17.3 | 12.4±2.6 | 184.5±12.7 |

### 3.3. Similarity-Based Classification Model

Based on the processed data and extracted features, a classification model is created. The flowchart detailing this classification model is presented in Figure 4.

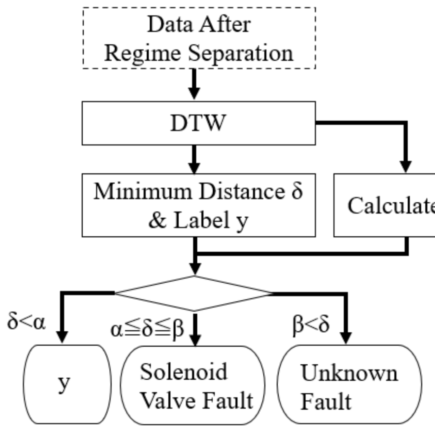


Figure 4 Classificaiton Process

The DTW algorithm is used to compute the distance from the test data to all the instances in the training data. Subsequently, the instance in the training data closest to the test data is determined. Classification of the test data is then accomplished using the label and distance of the closest data. If the minimum distance, denoted as $\delta_i$ , is greater than the threshold value $\beta$, it is considered an unknown falt. If $\delta_i$ is less than the threshold value $\alpha$, the label of the data closest to the distance is used as the label of the test data. If neither is the case, the data are considered to be a solenoid valve fault.

The threshold $\beta$ used for anomaly detection to identify unknown faults, is established from the maximum distance among known classes in the training data. Since the Unknown Fault data is not included in the training data, $\beta$ cannot be determined by hyperparameter tuning. Therefore, in this method, $\beta$ is determined by the 3σ rule (Pukelsheim, F.,1994) based on the distance $x_i$ from all known data. $\delta_i$ and $\beta$ are obtained by the following equations:

$$\delta_i = \min_{j \neq i} \left( DTW\left(X_i^{test}, X_j^{train}\right)\right) \quad (5)$$

$$x_i = \min_{j \neq i} \left( DTW\left(X_i^{train}, X_j^{train}\right)\right) \quad (6)$$

$$\mu_x = \sum_i x_i \ , \sigma_x = \sqrt{\frac{\sum_i (x_i - \mu_x)}{N}} \quad (7), (8)$$

$$\beta = \mu_x + 3\sigma_x \quad (9)$$

Here, $X_i^{test}$ is $i$-th test sample, $X_i^{train}$ is $i$-th training sample and $N$ equals to the number of training samples.

From the data analysis results in Table 1, $\delta_i$ is assumed to be 0 when the test data is in a known health condition. Therefore, α is set to 0.1 as a sufficiently small value considering numerical errors.

Contrary to healthy and bubble conditions, the data related to a solenoid valve fault vary in correlation with the valve open ratio. Consequently, the DTW distance can fluctuate even when dealing with the same type of solenoid valve fault. Based on these observations, it is inferred that a solenoid valve fault is present if the minimum distance falls within the range of $\alpha$ to $\beta$.

### 3.4. Feature Extraction

A method for estimating the location and degree of solenoid valve malfunction involves extracting the pressure drop magnitude $\Delta P$ upon valve opening. This feature is acquired from four sensors proximal to the valve (P3, P4, P6, and P7).

$$\Delta P_i = P_i(t_o - 0.001) - P_i(t_o) \quad (i=1,2,3,4) \quad (10)$$

Here, $P_i(t)$ represents the pressure at the position of the $i$-th solenoid valve at time $t$. Time $t_o$ corresponds to when the pressure drop transpires at one or more valves due to their opening.

The feature is formulated based on the physical principle stating that a decrease in valve opening leads to a reduced opening area, diminished flow velocity at the moment of valve opening, and a smaller pressure drop.

Figure 5 illustrates the instances of pressure data when a fault occurs at the valve 1 of the solenoid valve. As shown in the figure, the pressure drop reaches its peak at 100% valve opening and recedes as the valve opening diminishes. In contrast, the pressure drops of other valves - P4, P6, and P7 - remain unaffected by the faulty valve and maintain a relatively constant state. Consequently, the location of malfunctions can be determined.

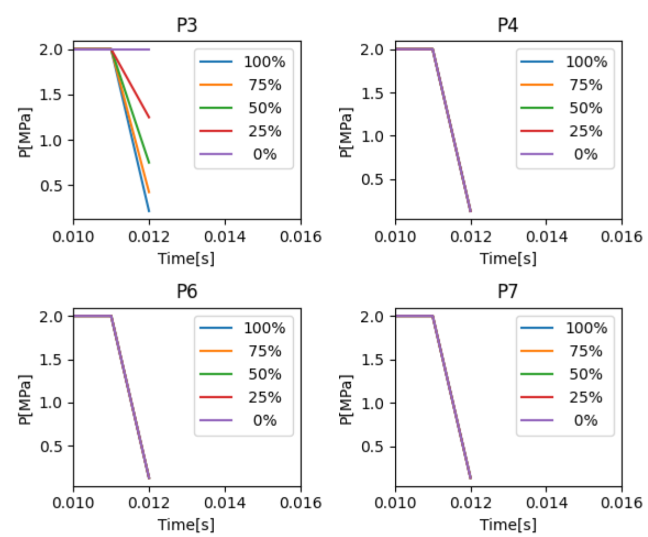


Figure 5 Pressure Drop Behavior with Solenoid Valve Fault at SV1 (P3), 0.010-0.012 sec

### 3.5. Valve Assessment Model

Based on the extracted features, The problematic valve locations are identified, the pressure drops of the four valves are compared, and the valve with the lowest pressure drop compared to the normal condition is the problematic valve location.

$$Location = \underset{i}{\operatorname{argmax}}\left(\Delta P_{i,Norm} - \Delta P_i\right)\ (i\text{=1,2,3,4}) \quad (11)$$

Here, $\Delta P_{i,Norm}$ represents $\Delta P_i$ under normal conditions.

Subsequently, the valve opening ratio for the fault location is estimated using polynomial regression.

$$Valve\ Open\ Ratio = \sum_{i=0}^{n} a_i \Delta P^i \quad (12)$$

The pressure drops at opening ratios of 0, 25, 50, 75, and 100% are known from the training data, n=4 is selected, and the coefficients $a_i$ are calculated from these data.

## 4. Results and Discussion

### 4.1. Results for Test data

The top five competition entries are listed in Table 3.

Table 3 Final Evaluation Result

| Rank | Team Name | Total Score |
|---|---|---|
| #1 | **LB** | 100.00 % |
| #2 | vibrationsensor | 99.94 % |
| #3 | SK | 99.86 % |
| #4 | Team Tsubasa | 99.05 % |
| #5 | KYU | 97.26 % |

The test dataset comprises information for spacecraft #4, which is not included in the trainnig data. However, the proposed methodology can also provide accurate estimates of this spacecraft.

Figure 6 shows the results of the δ calculations for the test data. These are categorized using threshold values β and α, according to the method outlined in Section 3.3.

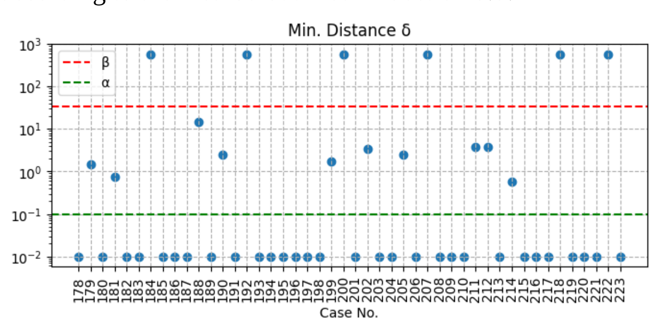


Figure 6 Minimum distance δ for test data ( δ <0.01 plotted as δ =0.001 for convenience)

Figure 7 illustrates the results of estimating the valve opening ratio based on the test data. This information can aid in constructing a regression equation based on the training data.

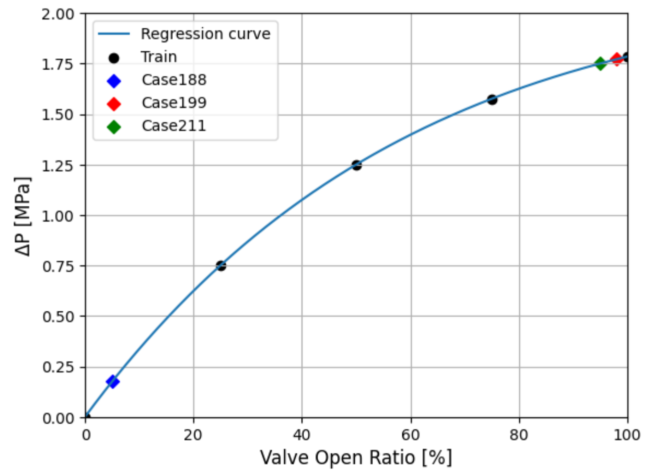


Figure 7 Δ P v.s. Valve Open Ratio for Solenoid Valve Fault at SV1

### 4.2. Limitations

Although the current study employs simulations with clean data, real-world data typically incorporate outliers and noise, necessitating preprocessing steps. Furthermore, in practical scenarios, multiple anomalies could occur simultaneously, calling for separate models to detect each distinct anomaly mode. Evaluating the model's diagnostic ability under varying valve opening and closing patterns will be crucial, considering that real-world operational conditions may differ from those in the training data.

## 5. Conclusions

This paper presents a winning solution for the The PHM Asia-Pacific 2023 Conference Data Challenge. The solution is based on the following concepts:

- Data regime separation based on in-class data variance
- Classification and anomaly detection based on similarity
- Physics-informed Feature design

The proposed architecture is designed to assess the health of a spacecraft propulsion system using pressure sensor data. Assurance of robust accuracy for unknown cases is accomplished by excluding data from regimes without inter-individual effects. The model, by leveraging similarity with known data, achieves anomaly detection for unknown classes and classification for known classes simultaneously. In addition, the model uses pressure drop features, designed based on domain knowledge, to estimate the degree of valve fault.

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