# Hybrid Approach of XGBoost and Rule-based Model for Fault Detection and Severity Estimation in Spacecraft Propulsion System

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## ABSTRACT

This study presents a method for fault detection and severity estimation of the spacecraft propulsion system. The spacecraft propulsion system is complicated, consisting of many valves, and operates in a harsh environment. Therefore, faults due to external factors such as bubbles or valve breakage can occur within the complex system at any time. To diagnose faults in this system, we propose a hybrid method of XGBoost-based method and rule-based method. In the XGBoost-based method, the overall fault classification, including unknown fault filtering was performed. In addition, the rule-based model was performed to estimate the fault severity. The results show that the proposed method reached a 99.94% score, which is calculated by the score matrix considering fault classification accuracy and severity estimation.

## 1. INTRODUCTION

Fault diagnosis of the system is essential since it helps keep it operating economically and safely, reducing maintenance costs and downtime. In systems that are complex and require high reliability, such as spacecraft propulsion systems, it is crucial to accurately identify faults' type, location, and severity. Moreover, it is essential to be prepared even for previously unobserved faults (Henry, 2008; Gueddi, 2017).


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Recently, research on fault diagnosis based on data-driven methods has been actively conducted and has shown excellent performance (He & He, 2017; Zhou, Zhang, Chen, & Bu, 2020). However, a purely data-driven fault diagnosis method might be inappropriate to be applied to the spacecraft propulsion system, which requires a high degree of reliability due to the risk of overfitting. Besides that, the general data-driven method might struggle to identify unseen faults. On the other hand, rule-based fault diagnosis has the advantage of being safe from the risk of overfitting, however, the disadvantage is that as the system becomes more complex, the rules become more complex and, therefore, more difficult to apply (Guo, Jin, Wu, & Zhao, 2019; Schein, Hirschberg, & Mandelbaum, 2006).
To address this challenge, we proposed a hybrid approach of data-driven and rule-based approach that can effectively diagnose faults and minimize the risk of overfitting. The remaining section of this paper is organized in the following way. The required background knowledge to understand the proposed method will be introduced in the next section. And then, the proposed method will be explained with a detailed description, and the results of our proposed method will be presented in the Results section. And the paper will be finalized with a Conclusion and Reference sections.

## 2. BACKGROUND

### 2.1. Principal Component Analysis (PCA)

A principal component analysis (PCA) is used for transforming multi-dimensional data to low-dimensional data while preserving the principal information of the data. The objective of the PCA is to discover an axis that can maximize the data variance. This axis is called principal component, and the first principal component can be calculated as Eq. (1) and (2):

$$\boldsymbol{p}_{k(i)} = \boldsymbol{x}_{(i)} \cdot \boldsymbol{w}_{(k)} \tag{1}$$

$$\boldsymbol{w}_{(1)} = \arg\max_{\|w\|=1}\{\sum_i (p_1)^2_{(i)}\} = \arg\max\{\frac{\boldsymbol{w}^{\mathrm{T}}\boldsymbol{X}^{\mathrm{T}}\boldsymbol{X}\boldsymbol{w}}{\boldsymbol{w}^{\mathrm{T}}\boldsymbol{w}}\} \tag{2}$$

where $\boldsymbol{p}$ is transformed principal component, $\boldsymbol{x}$ is the original zero-mean data, and $\boldsymbol{w}$ is the transformation weight. By reducing the dimension, a useful low-dimensional feature can be extracted from raw data, and this feature can be visualized.

### 2.2. Time Series Feature Extraction Based on Scalable Hypothesis Tests (TSFRESH)

A Time series Feature Extraction based on Scalable Hypothesis Tests (TSFRESH) is a python package that automatically extracts features from time-series data. The extracted features contain not only time-domain statistical features but also frequency-domain features such as minimum, maximum, mean, number of peaks, and spectral density. In addition, the TSFRESH provides filtered features that are relevant to the target labels. The selected features can be helpful in improving the performance of the data-driven models.

### 2.3. Extreme Gradient Boosting (XGBoost)

XGBoost, standing for Extreme Gradient Boosting, is a machine learning algorithm that utilizes the boosting technique to iteratively build a strong predictive model by combining multiple weak learners, typically decision trees, so that the model has excellent prediction performance and avoids the risk of overfitting. Also, by adding regularization terms, usually L1 or L2 norms, it limits the complexity of the model to prevent overfitting and improve generalization.

## 3. PROPOSED METHOD

### 3.1. Overall Process

The overall process of the proposed method can be divided into a training process and a test process, as shown in Figure. 1 and Figure. 2, respectively. The objective of the training process is to train an XGBoost model that can classify test data and acquire a regression equation that can estimate the severity of SV faults. On the other hand, the objective the test process is to filter unknown faults in test data and apply filtered data to the XGBoost model and the regression equation; thereby fault diagnosis in a spacecraft propulsion system can be made.

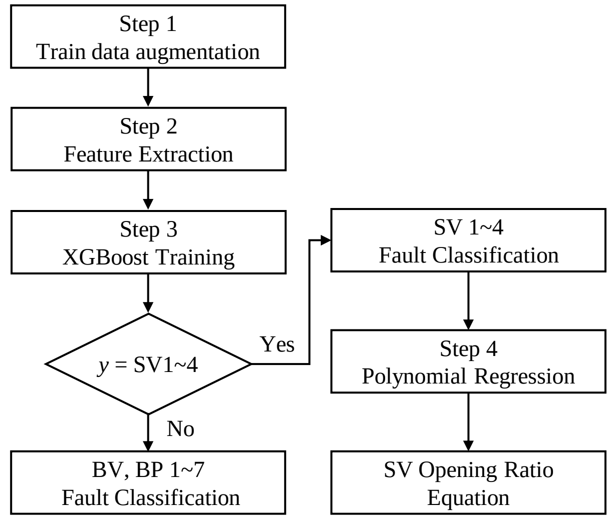


Figure 1. Overall Process of Training Process

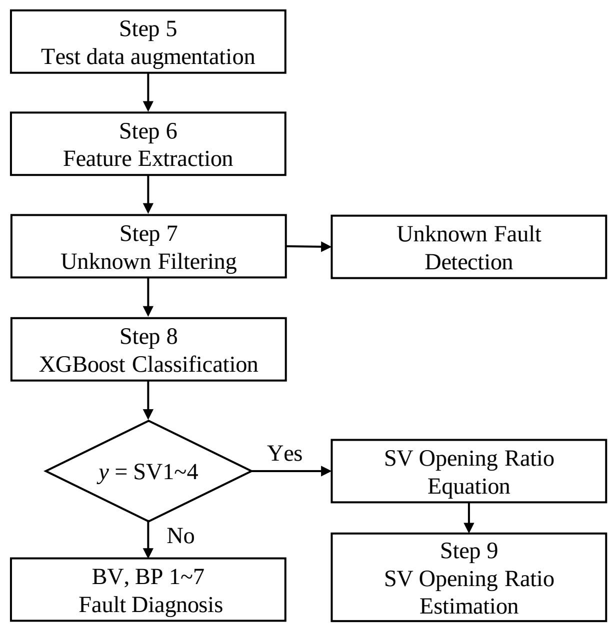


Figure 2. Overall Process of Test Process

The training process consists of four steps: 1) Train data augmentation 2) feature extraction step, 3) XGBoost training step, and 4) polynomial regression step. First, train data is augmented using a Gaussian filter to increase the number of data and generalization performance in a model training process. In the feature extraction step, features are extracted by using TSFRESH from training data. Then the XGBoost model is trained with the extracted features. Finally, a polynomial regression step was performed on the samples classified as solenoid valve (SV) faults in the previous step to derive a polynomial function formula to estimate the opening ratio of the SV.

The test process consists of five steps: 5) Test data augmentation, 6) feature extraction step, 7) unknown Filtering step, 8) XGBoost classification step, and 9) SV opening ratio estimation step. With the objective of increasing the test data, the test data augmentation was performed using Gaussian filter. In the feature extraction step, features are extracted by using TSFRESH from test data. In the unknown filtering step, unknown faults are filtered through the PCA using features extracted in the previous step. With the features of filtered test data, classifications are made using the XGBoost model, which was trained in the training process step 2. It should be noted that in this process, the final decision of classification was performed using hard voting among augmented test data. Finally, SV opening ratio estimation was performed on the samples classified as SV faults in step 6 using the SV opening ratio equation derived in step 3.

### 3.2. Data Augmentation

Data augmentation using Gaussian filter was used in both the training and test process as shown in Eq. (3). Through data augmentation, the number of data was increased five times compared to the given train and test data. Specifically, four Gaussian filters with sigma value, which is the standard deviation for Gaussian kernel, of 0.1, 0.2, 0.3, 0.4 were used.

$$g(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-x^2/(2\sigma^2)} \tag{3}$$

Here, $g(x)$ denotes the Gaussian filter and $\sigma$ denotes the standard deviation.

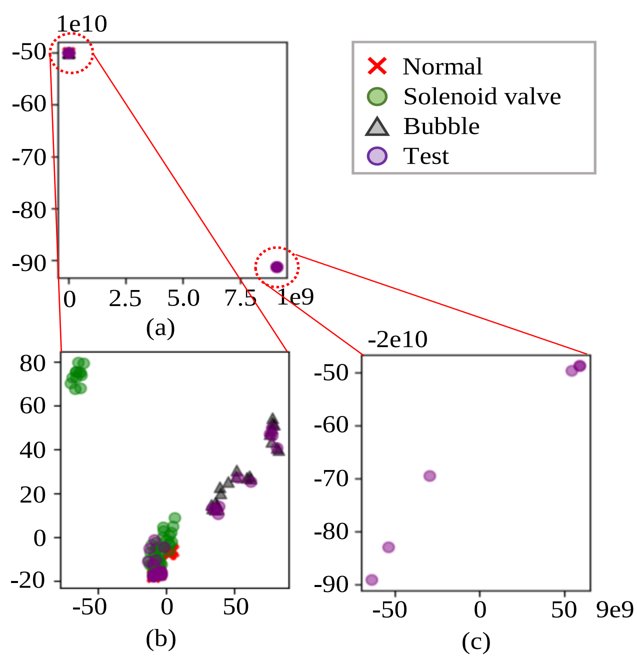


Figure 3. PCA results of (a) train and test data, (b) known train and test data, and (c) unknown test data.

### 3.3. Unknown Filtering

The unknown data is filtered by PCA results using TSFRESH features as described in Fig 3. The PCA results of all train and test data in Figure. 3(a) can be divided into two categories; Figure. 3(b) and Figure. 3(c). As shown in the figure, these two categories show a large Euclidian distance on the principal axis space, meaning that each category's instances have distinct features.

The category in Figure. 3(b) consists of train normal, train solenoid valve fault, train bubble fault, and test instances. On the other hand, the category in Figure. 3(c) has only test instances. Therefore, it can be inferred that the category in Figure. 3(c) is a known fault that is not contained in train data.

### 3.4. Regression of the Solenoid Valve Opening Ratio Using Polynomial Fitting Based on Physical Features

The pressure is a significant factor that is greatly influenced by the solenoid valve opening ratio. The solenoid valve fault with less opening during the opening range causes reduced pressure drop compared to a full opening because the restricted flow decreases the fluid's ability to pass through. Figure. 4 depicts the pressure remaining constant at 2.0MPa until 10ms within the opening range, but afterward, the pressure drop varies depending on the opening degree. Through this observation, we select the initial pressure drop slop ($f$) as a feature to identify the opening ratio.

The selected features exhibit linear relationships within the same solenoid valve. However, to account for nonlinearity caused by external noise and other factors, curve fitting was performed using a third-degree polynomial, as shown in Eq. 4 to determine the opening ratio of each solenoid valve.

$$\text{Opening Ratio} \approx \alpha f^3 + \beta f^2 + \gamma f + \varepsilon \tag{4}$$

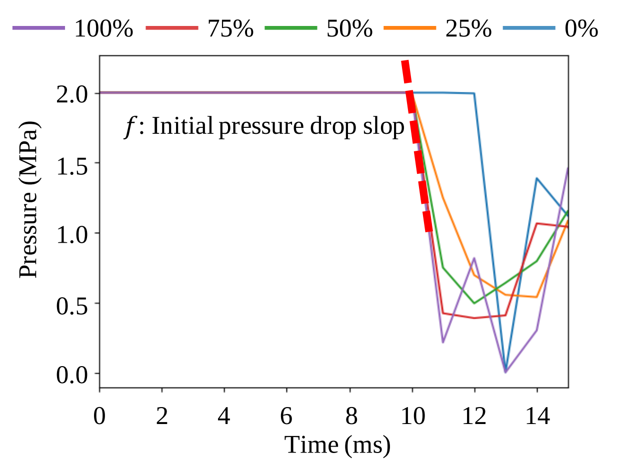


Figure 4. Physical Features of the solenoid valve 1 fault 0% to 100%

# 4. RESULT

## 4.1. Problem Description

Figure. 5 depicts an experimental propulsion system using water as the operational fluid used in this data challenge. The water is compressed to a pressure of 2 MPa and subsequently discharged through four solenoid valves (SV1 - SV4) that serve as thrusters. The pressure sensors labeled as P1 - P8 record time series data at a frequency of 1 kHz within the duration of 0-1200 ms

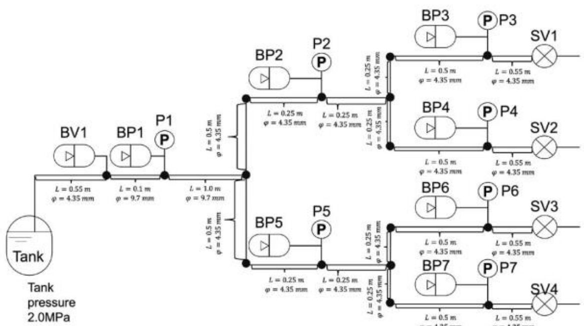


Figure 5. Illustration of the experimental propulsion system

## 4.2. Data Description

The training dataset encompasses normal and abnormal data from spacecraft No.1 to No.3. The test dataset comprises data from spacecraft No.1 and No.4. Each spacecraft has individual differences, such as the timing of opening and closing of solenoid valves, which leads to differences in the time series data. The training and test datasets both include data on normal conditions, bubble anomalies, and solenoid valve faults from different locations and severity. However, the test dataset additionally contains data on unidentified abnormal cases. The fault modes in train data are summarized in Table 1.

Table 1. Fault modes

| Number | Label | Description |
|---|---|---|
| 1 | Nor | Normal |
| 2~5 | SV1_0, SV1_25, SV1_50, SV1_75 | No.1 SV fault with four opening ratio |
| 6~9 | SV2_0, SV2_25, SV2_50, SV2_75 | No.2 SV fault with four opening ratio |
| 10~13 | SV3_0, SV3_25, SV3_50, SV3_75 | No.3 SV fault with four opening ratio |
| 14~17 | SV4_0, SV4_25, SV4_50, SV4_75 | No.4 SV fault with four opening ratio |
| 18~25 | BP1 ~ BP8, BV | Bubble contamination from eight locations |

## 4.3. Scoring Matrix

In the competition, the evaluation of the algorithm and model was assessed with the weighted summation of results of five tasks. For the first four tasks, task 1 (anomaly detection), task 2 (fault classification), and task 3&4 (fault isolation), the accuracy is set as an evaluation metric, and total score for each task is 10 points.

$$\boldsymbol{Eval}_{\boldsymbol{Task}\,1-4} = \frac{\sum_{\boldsymbol{i}=1}^{\boldsymbol{N_C}} (\boldsymbol{TP}_i + \boldsymbol{TN}_i)}{\boldsymbol{N}_{\boldsymbol{total}}} \tag{5}$$

where, $N_C$ denotes the number of classes, 2, 3, 8, and 4 for task 1 to 4, respectively; $N_{total}$ is the total number of test samples; $TP_i$ and $TN_i$ are true positive and true negative for class $i$.

Finally, task 5 (regression) is evaluated based on the absolute error between truth and prediction as shown in Eq. (6):

$$\boldsymbol{Eval}_{\boldsymbol{Task}\,5} = \max(-|\boldsymbol{truth} - \boldsymbol{prediction}| + 20, 0) \tag{6}$$

In the result of the evaluation metric of 5 tasks, the scores of spacecraft-4 that is not included in the training datasets, are doubled, considering the difficulty. Finally, scores from all tasks are combined and converted to a total score of 100 to derive a final score.

## 4.4. Training Result

In the training process, training data features extracted from TSFRESH were used as an XGBoost model input. Labels for the model training were given as 25 categories shown in Table 1. The result shows that the trained model shows 98.87% of validation accuracy during training. Misclassified data are cases that classify SV1_50 as SV1_75. Although misclassification is made during training, the trained model is well-trained because there was only a difference in severity where the type and location of the fault were properly classified. The purpose of the training process was achieved because the difference in severity could be solved through the regression model.

## 4.5. Linear Regression Result

The physical features are extracted from the training data corresponding to the valve positions with faults in the solenoid valve. For example, when SV1 had a fault, data from P3 were used. As no-fault data with a 100% opening ratio are available, features from normal data are used. Subsequently, third-degree polynomial fitting is performed on the extracted features, and the results are presented in Table 2.

In the test data, the data which is classified with the solenoid valve faults is fitted to third-degree curves specific to each solenoid valve position. The fitted results for the test solenoid valve fault features are illustrated in Figure. 6.

Table 2 The polynomial fitting results based on the physical features

| | $\alpha$ | $\beta$ | $\gamma$ | $\epsilon$ |
|---|---|---|---|---|
| SV1 | -0.1840 | -0.2518 | -0.4215 | 0 |
| SV2 | -0.1412 | -0.1857 | -0.3872 | 0 |
| SV3 | -0.1412 | -0.1857 | -0.3872 | 0 |
| SV4 | -0.1377 | -0.1759 | -0.3849 | 0 |

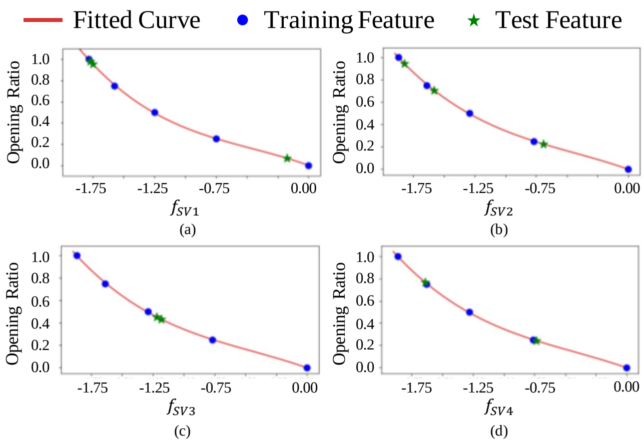


Figure 6. Test features fitted results for polynomial equations related to each valve position

### 4.6. Classification and Severity Estimation Result

Using the test data, the proposed method achieved a score of 99.94%. This score was calculated using a scoring matrix that considers both fault classification accuracy and severity estimation result.

## 5. CONCLUSION

In this work, the fault detection and severity estimation of the spacecraft propulsion system are addressed. Fault detection includes three tasks (anomaly detection, fault classification, and fault isolation), and severity estimation is a regression task. Fault detection is achieved by combining the time and frequency domain features with artificial intelligence. Severity estimation is performed by extracting the underlying physical meaning through the relationship between the pressure and the opening ratio. With the physics-informed data-driven model described above, our team achieved a score of 99.94%, placing second in this challenge.

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