Dataset Generation Based on 1D-CAE Modeling for Fault Diagnostics in a Spacecraft Propulsion System

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Abstract

The objective of this study is to generate a classified dataset of valve faults and bubble contamination anomalies in the propellant supply pipe of spacecraft propulsion systems. The dataset is available in PHMAP23, and the paper intends to describe its characteristics. The dataset includes time and pressure information and has been generated through numerical simulations using SimlationX, a 1D-CAE software. The condition of the propulsion system is reflected by the characteristics of the pressure dynamic response generated by the water hammer in the supply pipe caused by the rapid opening and closing of the downstream solenoid valve. Therefore, accurate classification of anomalies and faults can be achieved by extracting characteristics from the pressure dynamic response waveform.

1. Introduction

The Japan Aerospace Exploration Agency (JAXA) aims to obtain autonomous spacecraft technology for deep space exploration, including takeoff and landing on gravitational bodies. Health monitoring technology is essential, and we aim to enhance the Prognostic and Health Management (PHM) technology for the propulsion system, which is a critical subsystem. However, the amount of telemetry data that can be collected on the ground is quite limited due to restrictions on sensor installation and downlink capacity. To achieve on-board health monitoring, researchers are developing alternative, cost-effective sensors [1] and fault diagnosis methods [2-4] that require minimal learning data.

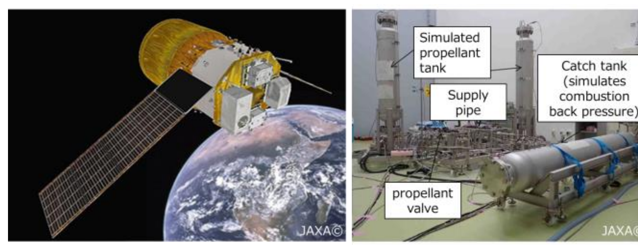

Figure 1. Evaluation of propulsion system dynamic response characteristics of a new H-II Transfer Vehicle (HTV-X).

One critical failure in spacecraft propulsion systems is a reduction in propellant supply to the main engines and attitude control thrusters. This failure is assumed to be due to an abnormal propellant valve behavior or filter blockage, and thrust is reduced only in the thruster downstream of the failed section. Quick response to abnormal modes is critical to maintaining the spacecraft's normal orbit and attitude.

Therefore, we focused on the pressure dynamic response caused by the propagation of water hammer in the supply pipe when the propellant valve is rapidly opened and closed, and identified the flow anomaly using the pressure response characteristics. However, if the apparent sound velocity of the working fluid is reduced due to the bubble contamination, the pressure wave propagation condition in the pipe will change, and the flow anomaly may not be accurately identified. In addition, the supply pipe system consists of multi-branch pipes, and there are many propellant valves as well. The open/close response of the propellant valve has a time variation for each individual propellant valve. This time variance may cause a disturbance on the pressure dynamic response in the pipes, preventing accurate determination of flow anomalies. In addition, it is difficult to obtain these data for a wide range of conditions in basic tests on the ground due to cost and time constraints, and new data construction methods utilizing numerical simulations are required. In particular, a large number of data with a wide range of parameters are needed for training in machine learning and other applications.

Therefore, this topic was set as the challenge for the data challenge. The objective of this paper is to develop a simple 1D-CAE modeling-based data set for fault diagnosis in a spacecraft propulsion system. A propulsion system was modeled on 1D-CAE using elements such as tanks, pipes, and valves. Calculations were performed using the model to generate time series data of the fluid pressure dynamic response due to water hammer when propellant valves were opened and closed. The test conditions were assumed to be valve closure faults, which can actually occur, and bubble contamination, which is not a fault but an anomaly that can affect fault diagnosis. To apply propulsion system fault diagnosis to spacecraft, it is necessary to classify these faults and anomalies without misdiagnosing them.

2. DATA SET GENERATION PROCESS

2.1. Model construction of a simple propellant supply system

JAXA has been developing model-based performance evaluation, risk analysis, and health monitoring methods for spacecraft propulsion systems [1-3,5], and has been conducting modeling and analysis using SimulationX [6], a multi-physics modeling tool that supports the Modelica® language.

For this data challenge, a simplified spacecraft propulsion propellant supply system was evaluated. A model of the propellant supply pipe was configured and numerical simulations were performed using SimulationX assuming one dimension. A simplified propulsion system model is shown in Figure 2, and the model configuration in the software is shown in Figure 3. The propellant supply system of a spacecraft propulsion system consists of tank, pipes, valves, and orifices. Pure water, which has a density and sound velocity close to that of hydrazine, the fuel, was used as the simulated working fluid. The pure water was pressurized at 2.0 MPaA from the upstream of a 10L tank. It is injected through solenoid valves (SV1-4) that simulate propellant valves at the thruster inlet, which is the most downstream part of this system. Each solenoid valve was downstream of a flow rate set to 18.0 g/s, equivalent to a 120 N RCS thruster fuel flow rate. The pipe outer diameter was 9.7 mm upstream and 4.35 mm downstream of the branch, as in the flight system. Pressure sensors are represented by P1-P8, while accumulator elements for introducing bubbles are represented by BP1~8. Since bubbles tend to accumulate in the branch pipes used to introduce pressure sensors, this condition is represented in the model by the amount of bubbles introduced into the accumulator element.

2.2. One dimensional numerical Simulation

Using the one-dimensional model described in section 2.1, the pressure dynamic response due to water hammer generated when a solenoid valve is opened and closed was

Table 1. Test conditions for training data

Spacecraft No.	Solenoid valves Opening Ratio /%	Solenoid valves duty ON/ OFF /ms	Bubble location	Note	Number of data
1	100	All 100/ 300	No	Normal	35
1	Any one 0 - 100	All 100/ 300	No	Fault	12
1	100	All 100/ 300	Any one	Anomaly	12
2	100	SV1: 101/ 299	No	Normal	35
2	Any one 0 - 100	SV1: 101/ 299	No	Fault	12
2	100	SV1: 101/ 299	Any one	Anomaly	12
3	100	SV1: 101/ 299 SV4: 99/ 301	No	Normal	35
3	Any one 0 - 100	SV1: 101/ 299 SV4: 99/ 301	No	Fault	12
3	100	SV1: 101/ 299 SV4: 99/ 301	Any one	Anomaly	12

Table 2. Test conditions for test data

Spacecraft No.	Solenoid valves Opening Ratio /%	Solenoid valves duty ON/ OFF /ms	Bubble location	Note	Number of data
1	100	All 100/ 300	No	Normal	10
1	Any one 0 - 100	All 100/ 300	No	Fault	5
1	100	All 100/ 300	Any one	Anomaly	5
4	100	SV2: 101/ 299	No	Normal	10
4	Any one 0 - 100	SV2: 101/ 299	No	Fault	5
4	100	SV2: 101/ 299	Any one	Anomaly	5
1	100	All 100/ 300	BP1 & BP3	Unknown Anomaly	1
1	100	All 100/ 300	Void	Unknown Anomaly	1
1	100	All 100/ 300	SV1 open delay long	Unknown Anomaly	1
4	100	SV2: 101/ 299	BP1 & BP3	Unknown Anomaly	1
4	100	SV2: 101/ 299	Void	Unknown Anomaly	1
4	100	SV2: 101/ 299	SV1 open delay long	Unknown Anomaly	1

obtained as time series data. Typical time series data are shown in Figure 4. The data was acquired with a sampling rate of 1 kHz and a sampling time of 0-1200 ms. The solenoid valve was set to open for 100ms and then close for 300ms. To reproduce the random variation in solenoid valve open/close time, a variation of 0.05 ms was introduced in theopen/close time control parameter for all valves. In addition, a 1 ms difference in open/close response time was added to certain solenoid valves to simulate individual differences in propellant valve open/close response time. The total time of opening and closing remains 400 ms even with the uncertainty. This sequence was repeated three times for a total simulation time of 1200 ms.

Tables 1 and 2 show the training and test data conditions. This data challenge included anomalies due to bubble contamination and solenoid valve opening fault. In addition, unknown anomalies are included in the test data. This is an anomaly mode that does not exist in the training data. The three conditions are: bubbles in BP1 and BP3 at two locations, a change in the gas fraction of the working fluid (sound velocity 750 m/s), and a long SV1 opening time delay.

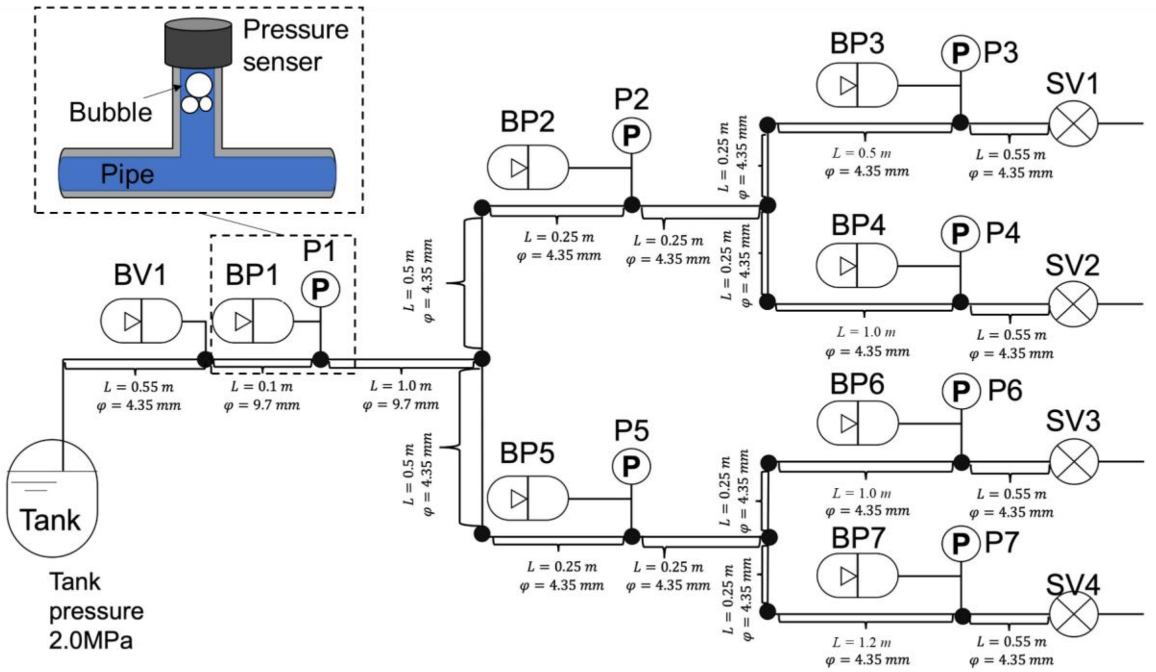

Figure 2. Schematic of propulsion system model.

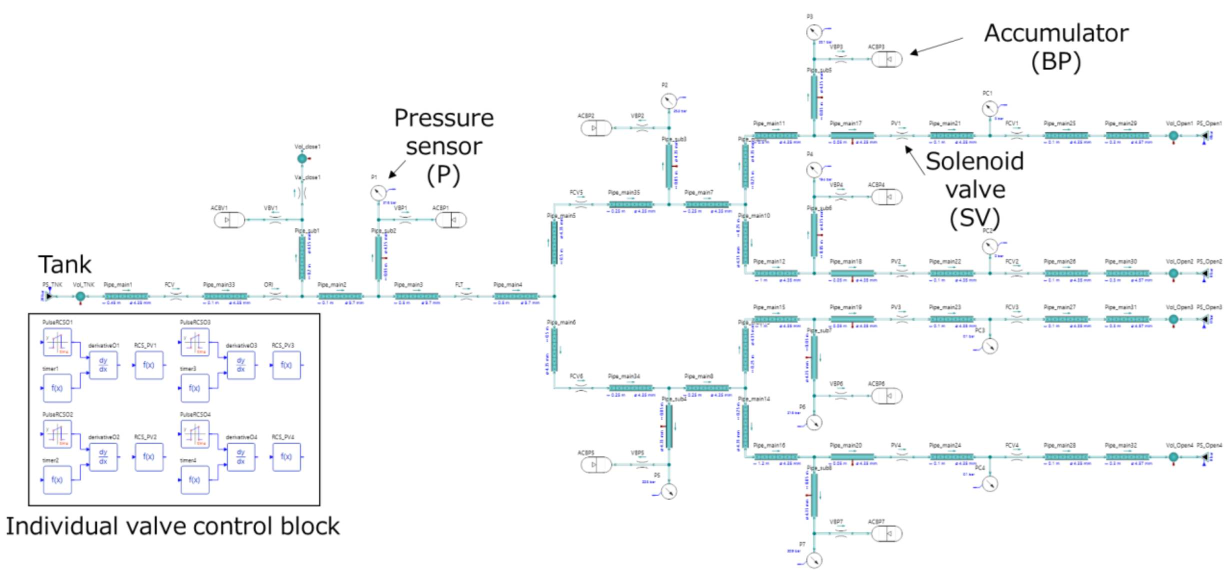

Figure 3. Propulsion system model configuration in 1D-CAE software.

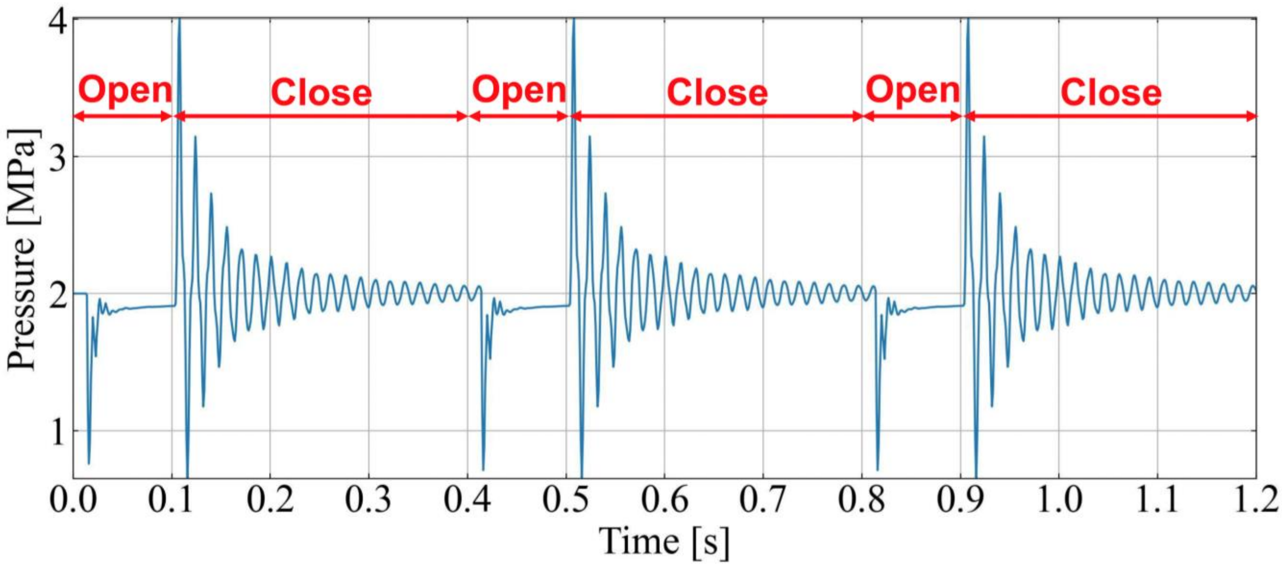

Figure 4. Time series data of typical pressure dynamic response in normal condition.

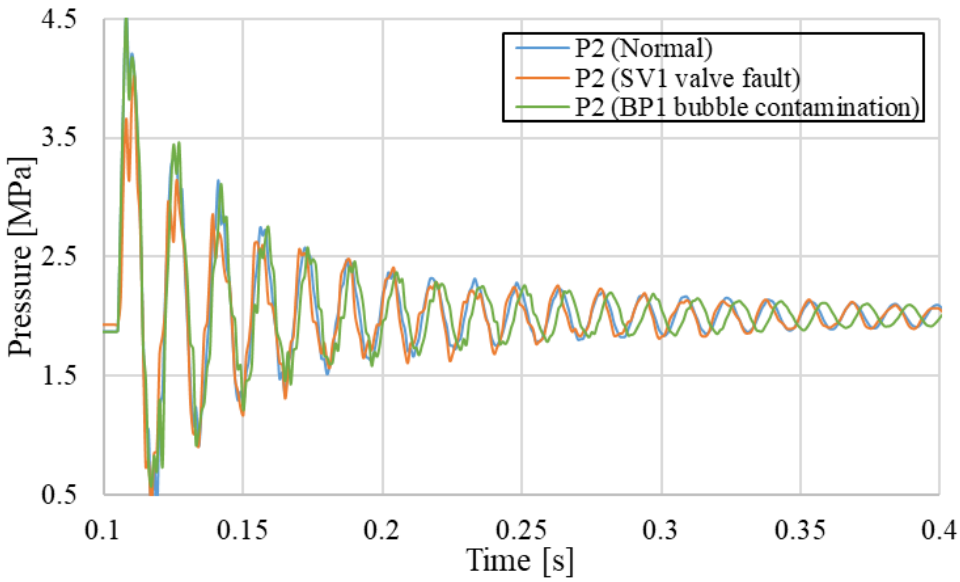

Figure 5. Comparison of pressure dynamic response when valve is closed (Normal, SV1 valve fault, BP1 bubble contamination).

<u>Bubble contamination anomaly</u>

During spacecraft operation, bubbles may contaminate the pipe due to dissolved of pressurized gas. Bubbles that cannot be redissolved remain in branch pipes. Their presence changes the apparent sound velocity in the pipe, causing changes in the time series data of the pressure dynamic response. Comparison of the pressure-dynamic response at close response time shown in Figure 5 confirms the characteristics of the wave period slightly different from that of the normal condition. Bubble contamination and its location should be detected. In this data challenge, as shown in Figure 2, eight locations are considered as candidates for bubble introduction locations, BV1 and BP1 to BP7, and are given as accumulator components. For simplicity, the amount of bubble contamination was set constant (2 MPaA, equivalent to 0.5 mL) in all cases.

<u>Solenoid valve fault</u>

This is one of the major and mission-critical failure modes in spacecraft propulsion system. It is necessary to quickly determine which solenoid valve (propellant valve) has failed, especially during orbit transfer maneuvers or other time critical situations. Solenoid valves normally open and close at 100% and 0% open/close, respectively, for ON/OFF control. If a fault occurs, since the solenoid valve opens and closes at an arbitrary value between 0% and 100%, The flow rate is reduced. A comparison of the pressure dynamic response at close response time in Figure 5 confirms the different characteristics of the peak values from those under normal conditions.

Unknown anomalies and faults

On orbit, completely unexpected and unknown anomalies and faults can occur as I mentioned before. It is necessary to distinguish these from known anomalies and faults, without confusing them with known anomalies and faults, in order to make an accurate handling of the situation. Some unknown anomalies and faults may be mixed in with the test data. Identifying them is one of the tasks of this data challenge.

Individual differences in spacecraft

Since solenoid valves have individual, hardware-to-hardware differences in the timing of opening and closing, the time-series data of the pressure dynamic response obtained from the same spacecraft propulsion system design will differ, and these differences will become the individual differences of the spacecraft. In this data challenge, four spacecraft (No.1 to No.4) were targeted for the series satellites, and individual differences between hardware were given. The results of three of them (No.1 to No.3) are included in the training data, while the test data consists of the results of No.1 and No.4.

3. STRUCTURE OF DATA SET FILE

The dataset is saved at this URL (https://phmap.jp/wp-content/uploads/2023/05/dataset.zip) in the configuration shown in Figure 6. The data is provided in comma separated value (CSV) files. The time series data obtained from the pressure sensors are saved with their labels in separate files for each test case number. The test conditions for each test case are saved in labels.xlsx. The structure of the CSV file is as follows: Column A contains the sampling time (0-1.2s), and columns B through H contain the pressure sensor time series data from P1 through P7 shown in Figure 2.

```
dataset
├ train
│  ├ data
│  │  └ Case1~177.csv
│  └ labels.xlsx
├ test
│  ├ data
│  │  └ Case178~223.csv
│  └ labels_spacecraft.xlsx (Only spacecraft No. provide)
├ submission.csv
└ readme.pdf
```

Figure 6. Dataset folder structure

4. CHALLENGES AND EVALUATION METRICS

In the PHMAP23 Data Challenge, the challengers were tasked with the following items.

1) Classification of normal/abnormal condition.

   Correct classification provides 10 points for each case.

2) For the data detected as abnormal, determine if it is an anomaly due to bubble contamination, solenoid valve fault, or unknown fault.

   Correct classification provides 10 points for each case (only for the data correctly detected as abnormal.)

3) For the data identified as bubble contamination, determine the location of the bubble from eight locations, BV1, and BP1 to BP7.

   Correct location identification provides 10 points for each case (only for the data correctly identified as bubble contamination.)

4) For the data identified as solenoid valve fault, determine which of the four solenoid valves (SV1 to SV4) failed.

   Correct valve identification provides 10 points for each case (only for the data correctly identified as solenoid valve fault.)

5) For the solenoid valve identified as a fault, predict the opening ratio Y[%] (0 <= Y < 100).

   Prediction of the opening ratio provides

$$\max\left(-\left|Y_{\mathrm{truth}} - Y_{\mathrm{prediction}}\right| + 20, 0\right) \tag{1}$$

   points for each case (only for the solenoid valve fault cases where the abnormal valve is correctly identified.)

- For spacecraft-4, all scores are doubled, considering the difficulty.

5. CONCLUSION

This paper describes the method and features of generating pressure dynamic response data inside the propellant supply pipes of a spacecraft propulsion system, which was provided for the data challenge. It is hoped that this data challenge will lead to the development of meaningful methods in academia and industry, and that the field of PHM will become more and more active. Since the data in this paper is open to the public worldwide, we hope that it will be of great use in the future, and we would greatly appreciate it if it could be a trigger for exchanges among the various communities.

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SimulationX. https://www.simulationx.com/

BIOGRAPHIES

Kohji Tominaga received his master's degree in aerospace engineering from Waseda University in 2021. He started his career at Japan Aerospace Exploration Agency (JAXA) Research and Development Directorate in 2021 as a member of Spacecraft Propulsion Engineer. His main research interests are related to unstable ignition phenomena in bipropellant thrusters and prognostics and health management of spacecraft propulsion systems.

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