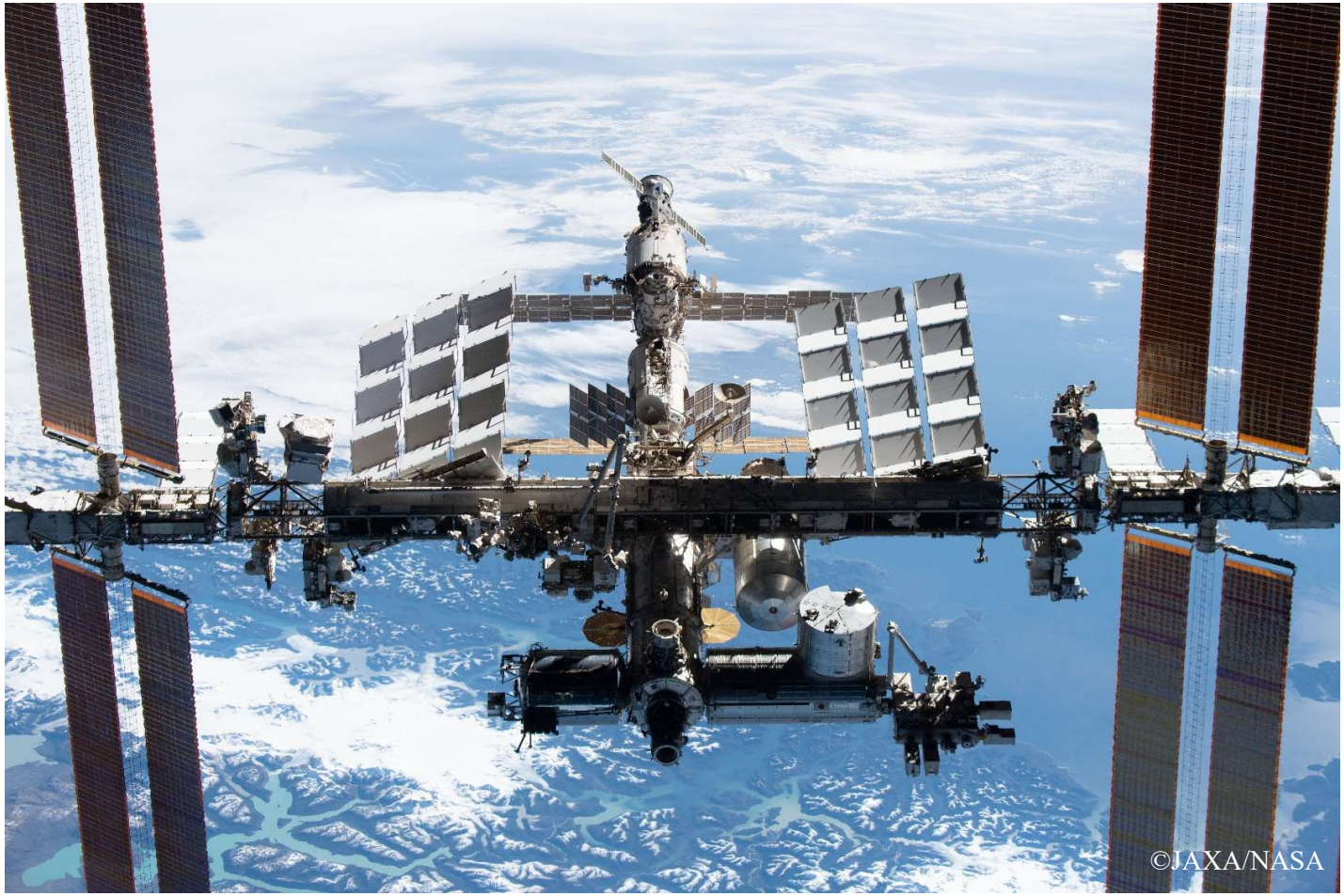
FRAMily 2022, Kyoto

Explainable symptom detection in telemetry of ISS with FRAM, Random Forest and SpecTRM



Shota Iino, Hideki Nomoto,
Takayuki Hirose, Yasutaka Michiura

Japan Manned Space Systems Corporation (JAMSS)

Going to Moon, Mars, and further

3:16:50

1. Introduction

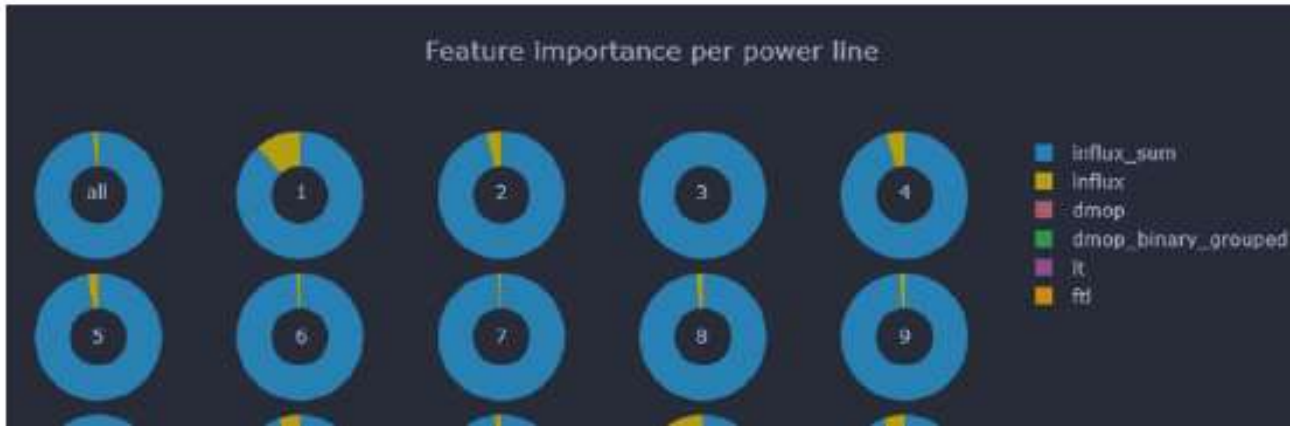
Most of anomaly are caused by interactions of multiple variables.

Flight controllers cannot detect several anomaly symptoms with single telemetries.

Automatic symptom detection to assess unusual telemetry trends.

2. Related works

Kostovska's interpretable analysis of spacecraft telemetry (GalaxAI)



(Kostovska, 2021)

Some authors proposes methods of anomaly detection,
but the explainability is often lacking in those approaches.

3. Methodology

A new method for explainable symptom detection

FRAM

Modeling the complex system to understand causal relationships of telemetries

Random Forest

Conducting symptom detections with machine learning

SpecTRM-RL

Explaining the rationale of the symptom detection

① FRAM (Functional Resonance Analysis Method)

(Hollnagel, E. (2012))

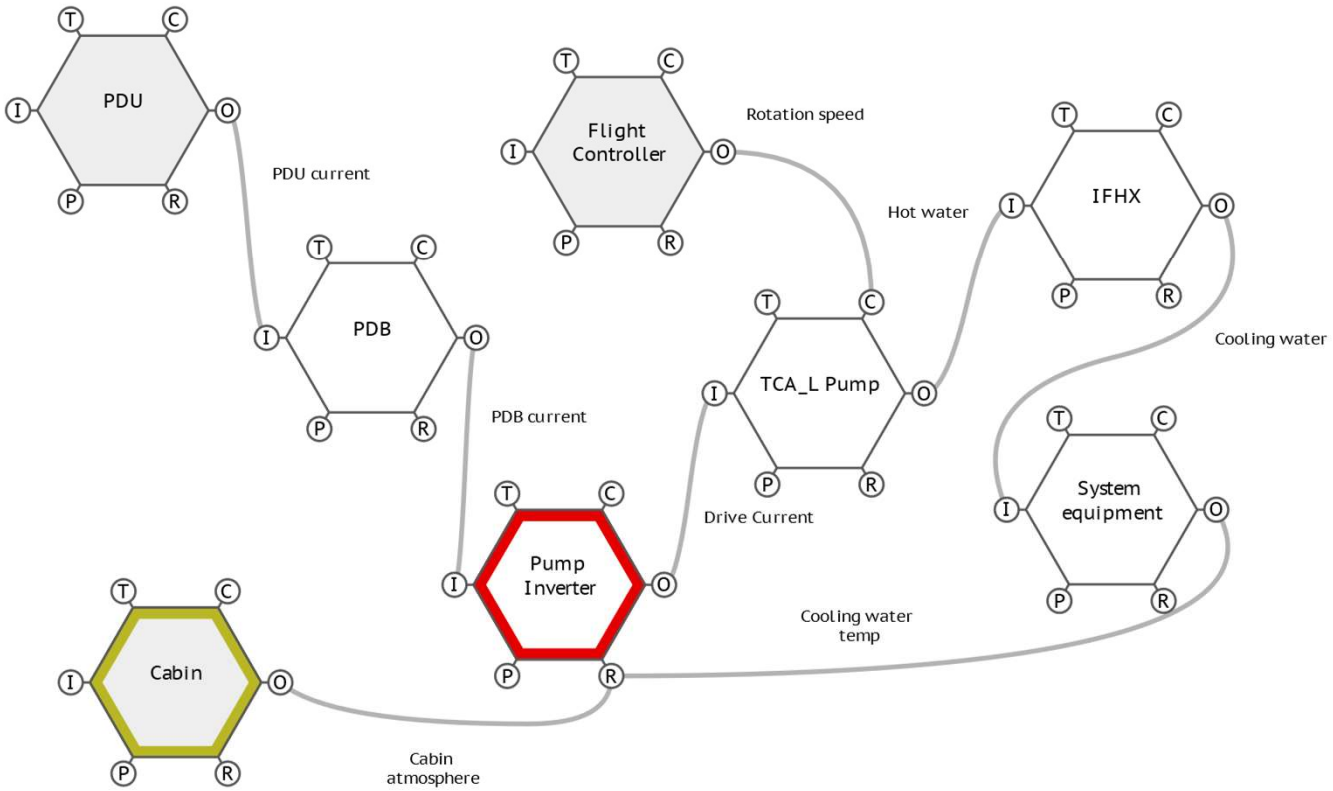


Table 1. Six aspects of FRAM.			
Class			6 aspects
Input	Trigger		Input
	Prior condition		Precondition
	Posterior condition	change output	Control
		stop output	Resource
			Time
Output			Output

FRAM modeling of the system to understand causal relationships of telemetries **(more than 100 telemetries)**

② Normal behavior model (Ex. Random Forest)

1. Normal behavior model development

$$\hat{y}_t = f(\boldsymbol{x}_t)$$

Predicted normal value of objective variable at time t

Normal behavior model developed by Random Forest regression and past normal telemetry data

Measured values of explanatory variables at time t

2. Prediction error calculation and symptom detection

$$e_t = y_t - \hat{y}_t$$

Prediction error of objective variable at time t

Measured value of objective variables at time t

If $|e_t|$ exceeds pre-defined threshold δ, it is judged as a sign of anomaly.

③ SpecTRM-RL (Specification Tools and Requirement Methodology-Requirement Language)

(Leveson, N. (2003))

OR

AND

	Conditions			
Nominal	Temperature < 10	T	T	F
	Humidity < 30	*	T	T
Off_Nominal	Temperature < 10	T	F	
	Humidity < 30	F	F	

**** INCOMPLETE ****	Temperature < 10	F	
	Humidity < 30	F	
**** INCONSISTENT ****	Temperature < 10	T	
	Humidity < 30	F	

T… True
F… False
*… True or False

- Integrity check in INCOMPLETE showed the combinations of conditions were not included.
- Consistency check in the INCONSISTENT showed the states which does not have unique transition with combinations of parameters.

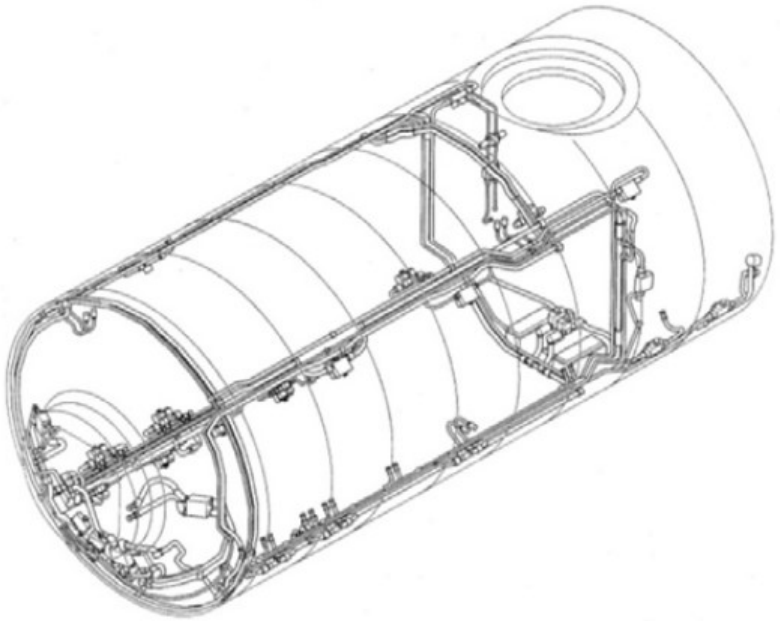
SpecTRM-RL(one of the formal methodologies) shows the possible rationales of symptom detection.

4. Experiment

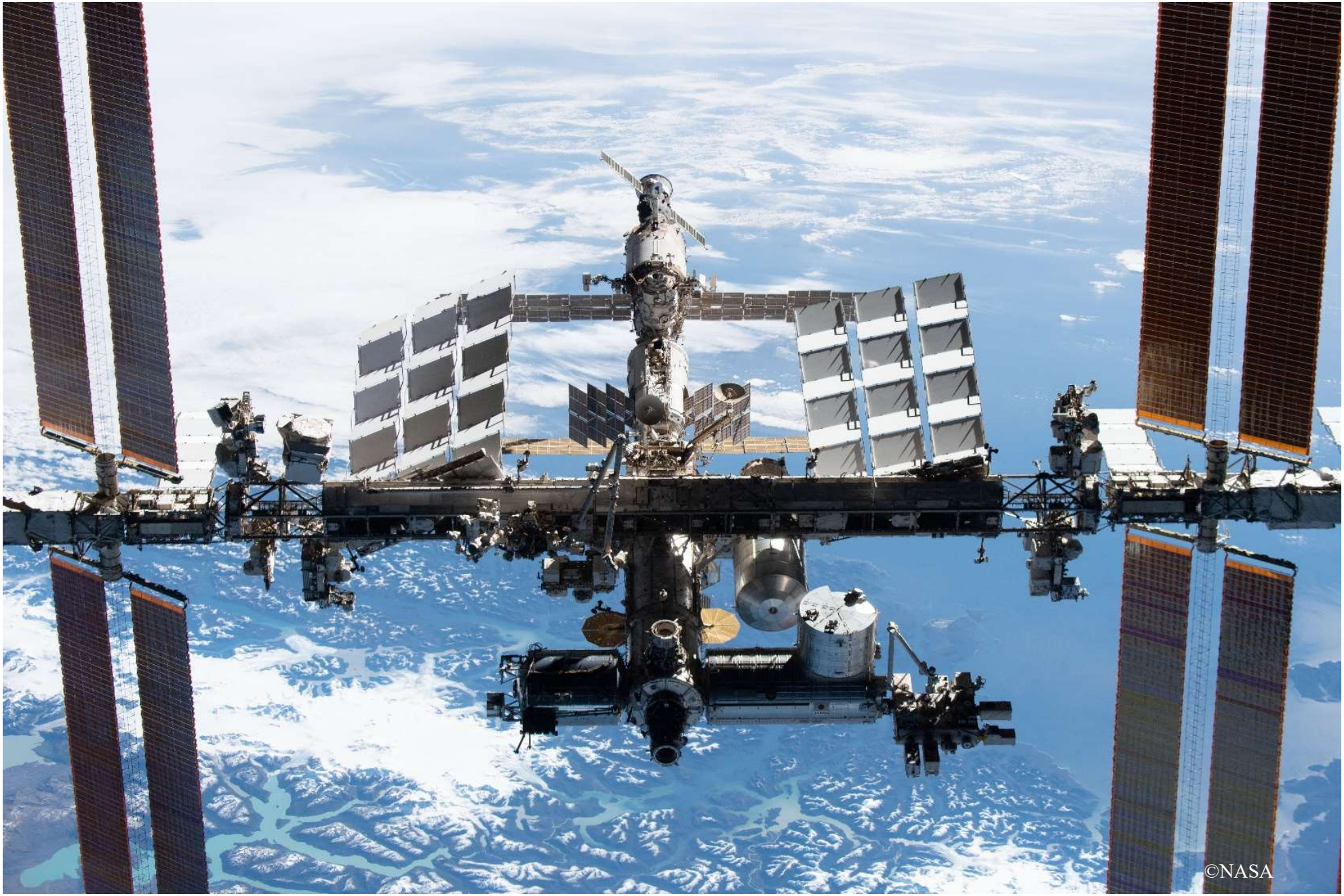
- A **pump inverter of Thermal Control Assembly - Low (TCA-L) of Japanese Experiment Module (JEM)** failed in 2012.
- This anomaly was caused by **multiple factors**.
- We explored whether we could detect symptoms of the anomaly.

Number of records of telemetry data.

	Period	Number of records
Train	2011/11/6-2012/1/30	3,725,381
Test (1st half)	2012/1/31-2012/3/1	2,421,955
Test (2nd half)	2012/3/1-anomaly	



(JAXA, 2013)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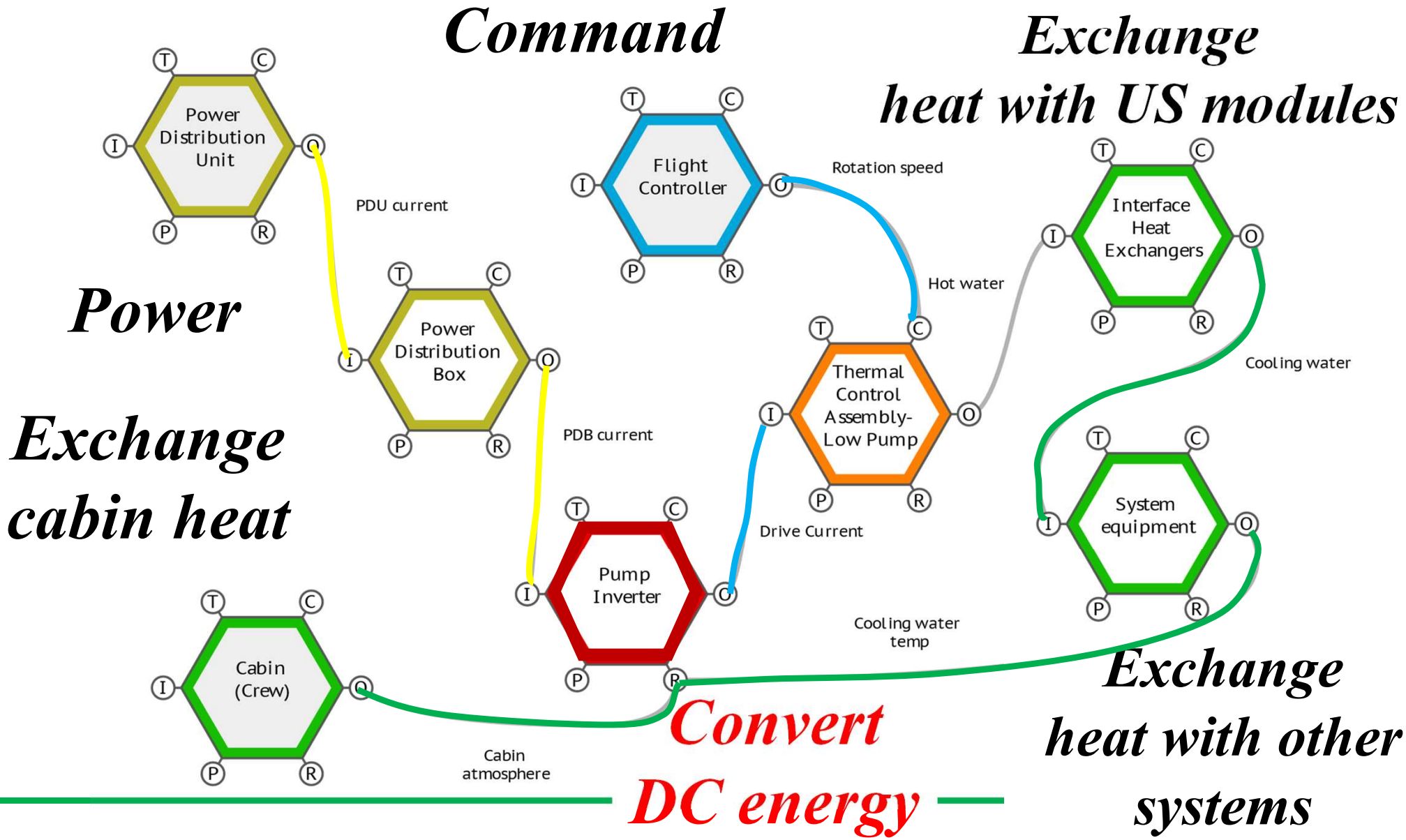
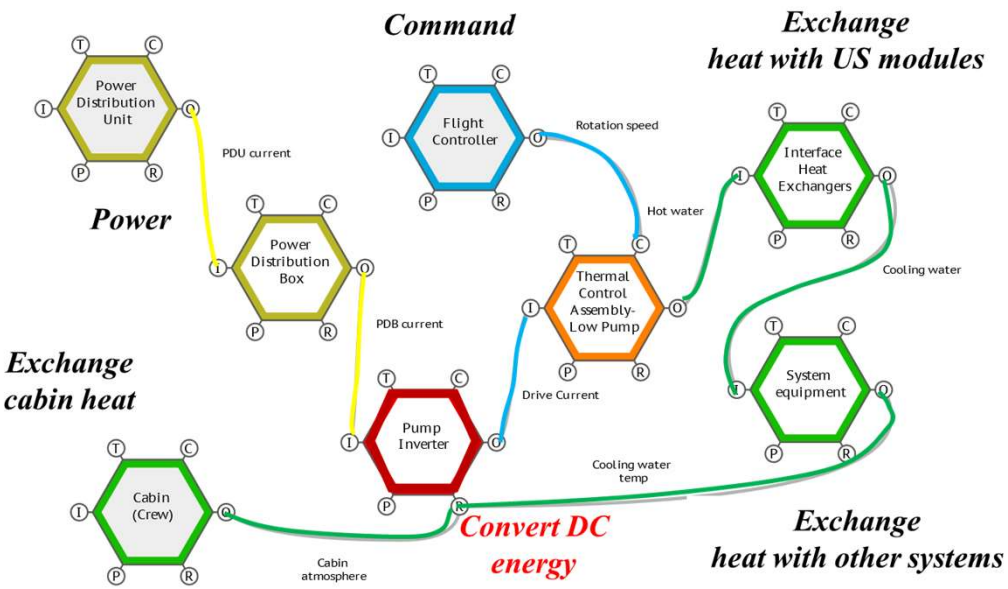
Step 1: Selecting telemetries

System modelling by FRAM

FRAM model represents dependency among functions



Step 1: Selecting telemetries



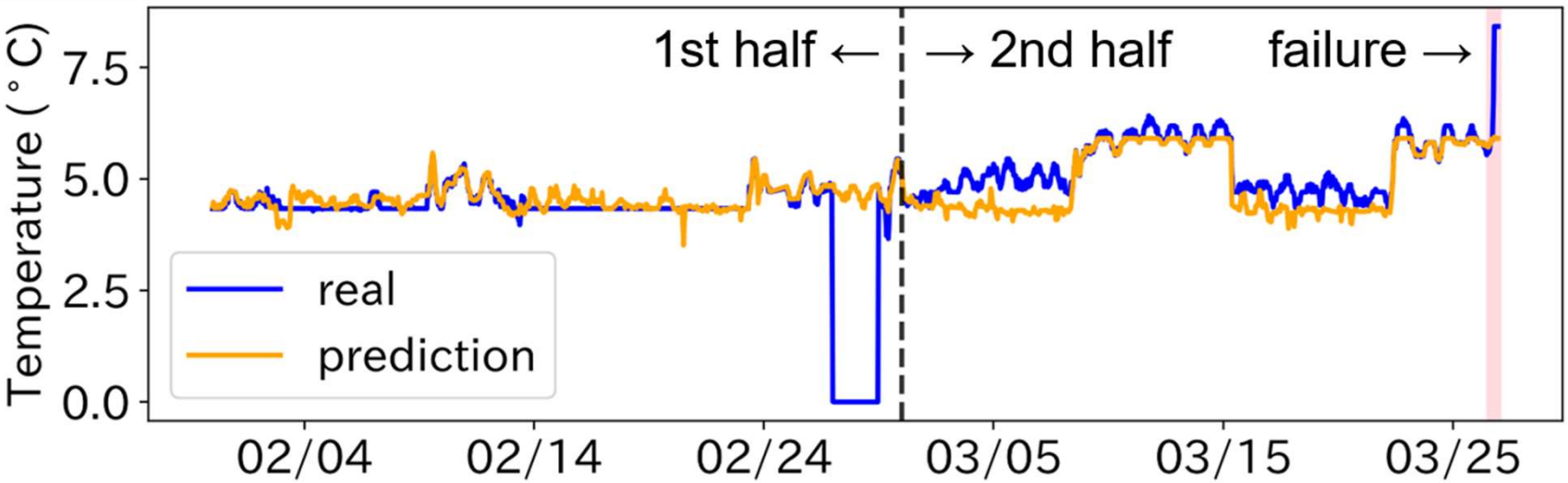
System modelling by FRAM

FRAM model represents dependency among functions related to the pump inverter.

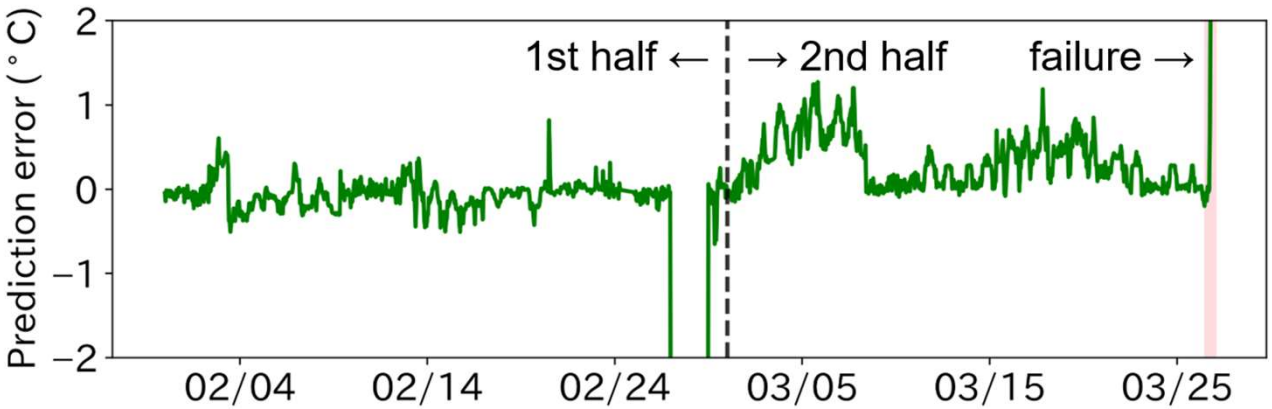
	Telemetry name	Explanation
1	Temperature of pump inverter	Analysis target
2	Service module PPH2O	Causes of condensation
3	Cabin temperature	
4	Condense out pressure of water separator	Related to the temperature of pump inverter
5	Cabin heat exchanger coolant out temperature	
6	Cabin heat exchanger flow rate	

Selecting telemetries for symptom detection

Step 2: Normal behavior prediction

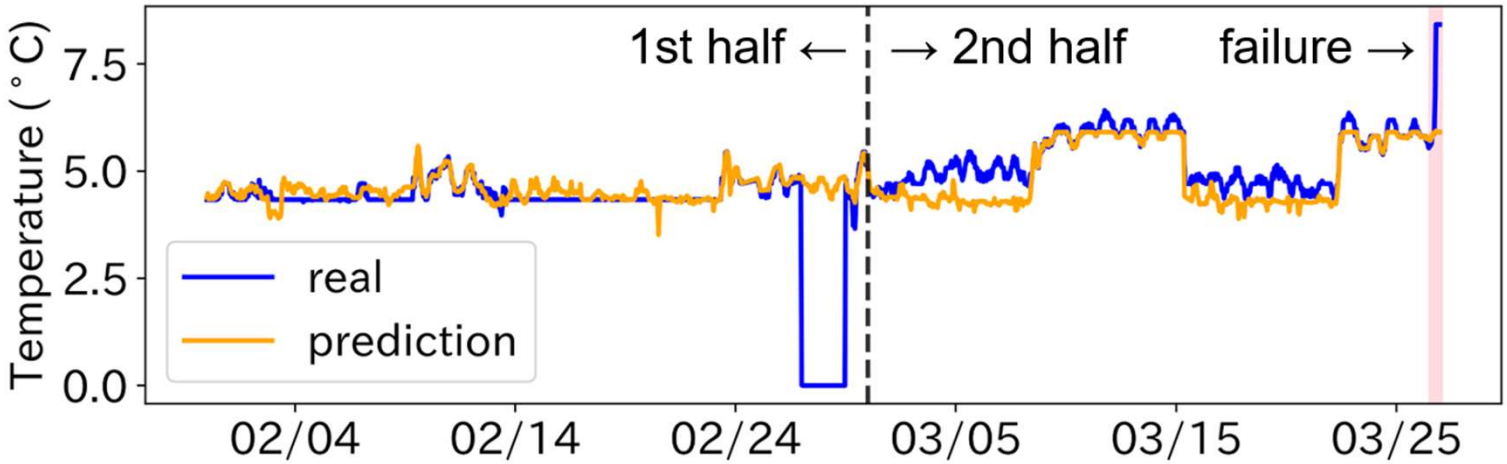


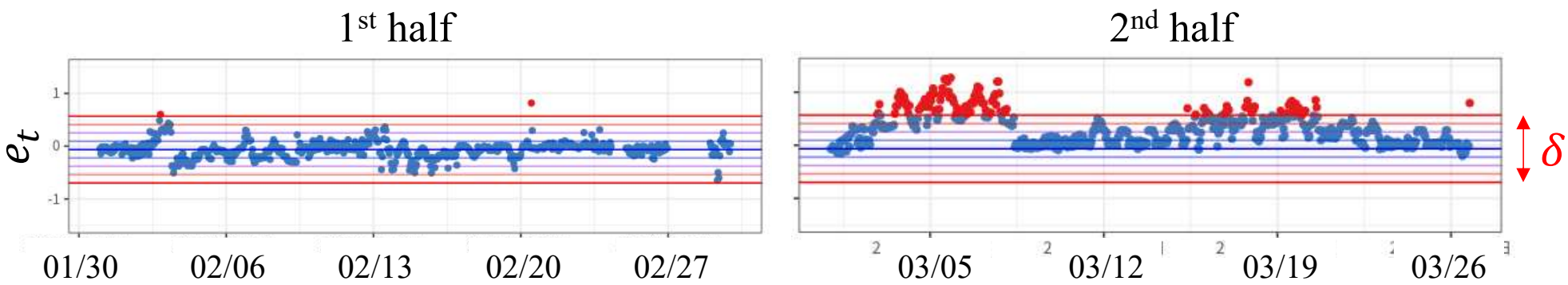
The normal behavior model successfully reproduces overall trend of the pump inverter temperature.



Prediction error gets larger in the period just before failure (the 2nd half of the test period), implicating sign of anomaly.

Step 3: Symptom detection



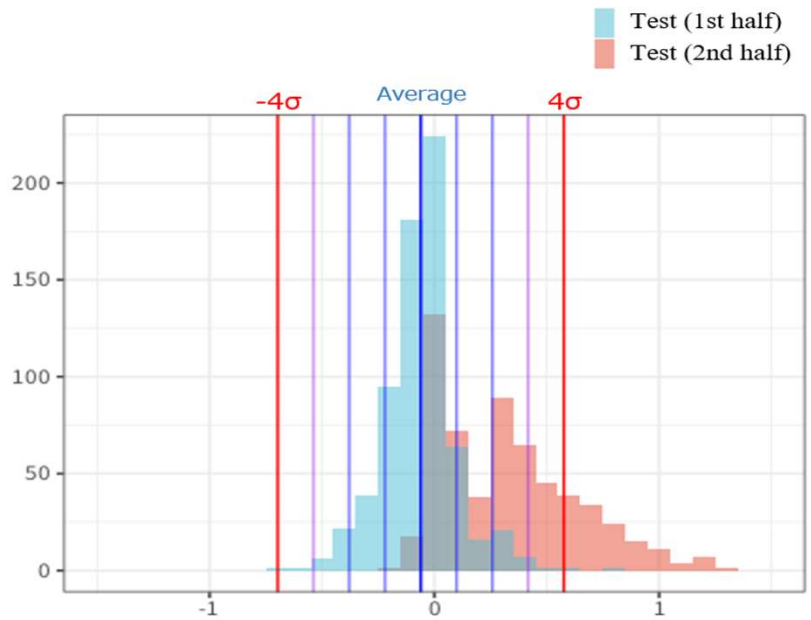


● Alarm ($|e_t| > \delta$)

With the threshold $\delta = 4\sigma$, where σ is the standard deviation of e_t in normal period, number of alarm ($|e_t| > \delta$) is quite small

Number of alarm substantially increases, indicating symptoms occurs in the 2nd half.

Statistical analysis of prediction error and alarms



Histogram of prediction error

	Probability of appearance	Range
Average	—	-0.060
σ	—	0.159
∓σ	76.6%	-0.220～0.099
∓2σ	93.2%	-0.379～0.258
∓3σ	99.1%	-0.538～0.417
∓4σ	99.7%	-0.697～0.576

99.7% of data points fall within the range μ ± 4σ.

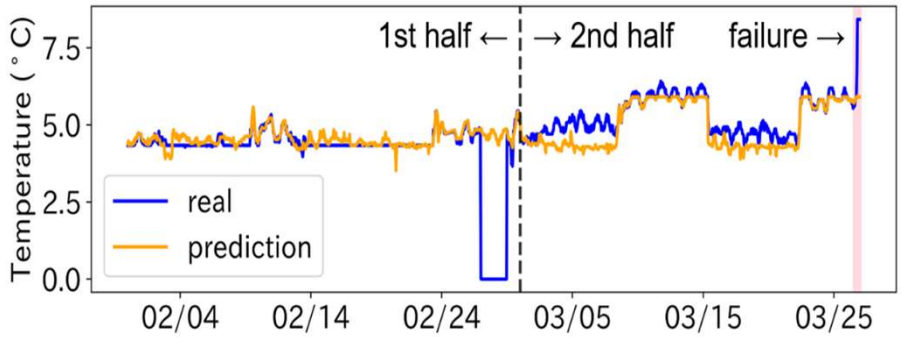
Simulation results of alarms

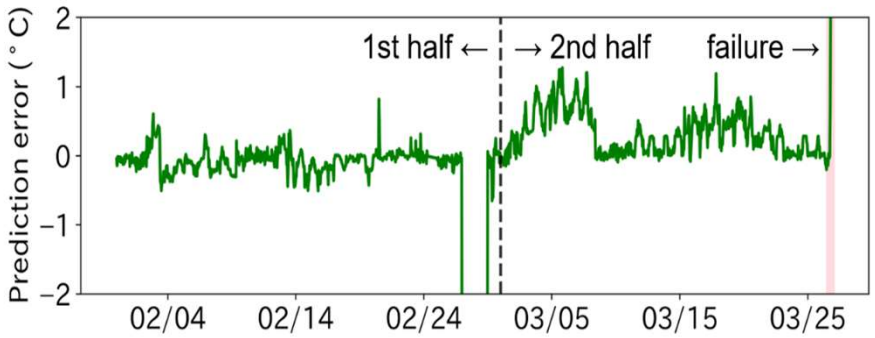
Standard deviation	Range	Alarms (1st half)	Alarms (2nd half)
∓σ	-0.220～0.099	159/680	403/595
∓2σ	-0.379～0.258	46/680	329/595
∓3σ	-0.538～0.417	6/680	196/595
∓4σ	-0.697～0.576	**2/680**	**128/595**

128 alarms were detected in the second half.

Step 4: Explaining the reason of detection

Symptom detection by Random Forest





Explaining the reason of detections

① Feature importance of RF

Explanatory variable	Importance
Service module PPH2O	0.684
Cabin temperature	0.202
Condense out pressure of water separator	0.045
Cabin heat exchanger coolant out temperature	0.037
Cabin heat exchanger flow rate	0.032

② SpecTRM-RL analysis

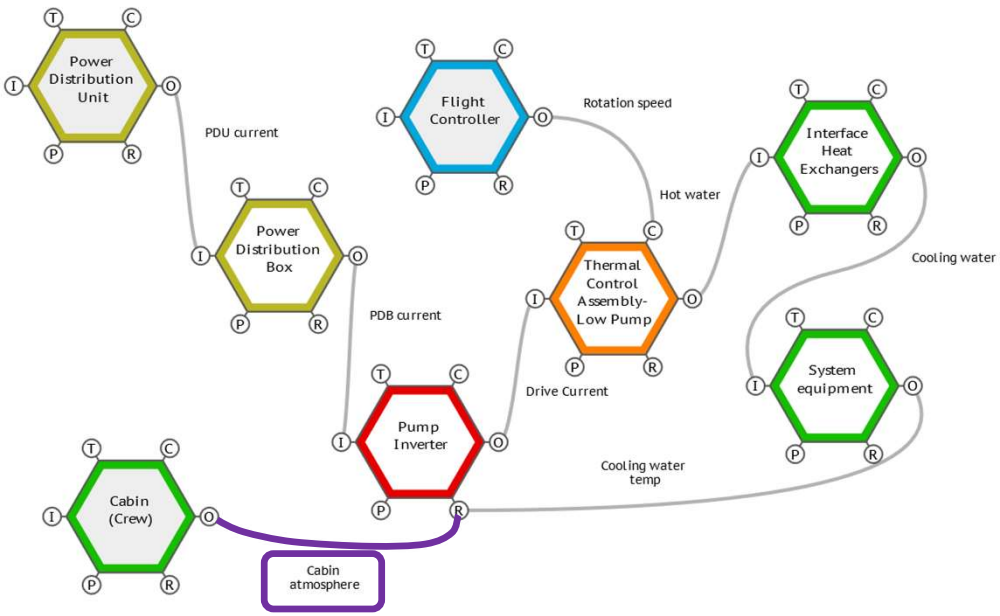
**** INCOMPLETE ****	Service module PPH2O < (A)	*	*	F	*	F	*	T
	Cabin temperature < (B)	*	F	*	T	T	T	T
	Condense out pressure of Water separator < (C)	F	T	T	T	T	T	T
	Temperature of pump inverter is between (D) & (E)	*	*	*	F	T	T	T
	Cabin heater exchanger coolant out temperature < (F)	*	*	T	*	F	T	F
	Cabin heater exchanger flow rate < (G)	*	F	T	F	*	F	F
**** INCONSISTENT ****	Service module PPH2O < (A)	*						
	Cabin temperature < (B)	F						
	Condense out pressure of Water separator < (C)	T						
	Temperature of pump inverter is between (D) & (E)	F						
	Cabin heater exchanger coolant out temperature < (F)	F						
	Cabin heater exchanger flow rate < (G)	T						

Feature importance of Random Forest

Explanatory variable	Importance
Service module PPH2O	**0.684**
Cabin temperature	**0.202**
Condense out pressure of water separator	0.045
Cabin heat exchanger coolant out temperature	0.037
Cabin heat exchanger flow rate	0.032

- Service module PPH2O (**vapor pressure**) and cabin temperature were important for prediction in the normal state.

- **It is consistent with expert knowledge**



Analysis results by SpecTRM-RL

Normal	Service module PPH2O < (A)	T	T	*	T	T	T	F
	Cabin temperature < (B)	*	T	F	F	T	F	*
	Condense out pressure of Water separator < (C)	T	T	T	T	T	T	T
	Temperature of pump inverter is between (D) & (E)	*	*	T	F	F	T	F
	Cabin heater exchanger coolant out temperature < (F)	T	F	F	*	T	T	F
	Cabin heater exchanger flow rate < (G)	T	T	T	T	T	T	T
		109	248	389	332	23	21	25
Abnormal	Service module PPH2O < (H)	T	F					
	Cabin temperature < (I)	F	F					
	Condense out pressure of Water separator < (J)	T	T					
	Temperature of pump inverter is between (K) & (L)	F	F					
	Cabin heater exchanger coolant out temperature < (M)	F	F					
	Cabin heater exchanger flow rate < (N)	T	T					
		118	10					

- In normal conditions, there is no particular characteristic in the combinations. Not only True also False exists in each condition.
- In abnormal conditions, **unique characteristics** in the combinations exist.
- 3 conditions related to causes of **condensation had all False** and **Service module PPH2O** also had some False in the period.

Future application

- Deep space missions require **autonomous operations to cope with long communication delays.**
- Our interpretable method can contribute to **health monitoring of space systems and symptom detection with reasoning of detection.**
- It is expected to widely contribute to the safety of related systems.

A Future Vision of a Fully Developed Lunar Economy.
Image Credit: JAXA

6. Conclusion

- We proposed **a new method for explainable symptom detection combining FRAM and SpecTRM-RL with Random Forest.**

- The method enables us to carry out **systemic analyses with the reasoning of symptom detections overcoming the limitations** of previous studies.

- We verified the proposed method with an experiment with the data of the thermal control system of JEM in 2012.

Best paper in track award at IEEE Aerospace conference

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2022 IEEE Aerospace Conference
Best Paper in Track Award

Track 11: Diagnostics, Prognostics and Health Management (PHM)

for excellence in technical innovation and presentation

"Explainable Symptom Detection in Telemetry of ISS with Random Forest and SpecTRM"

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Shota Iino, Hideki Nomoto, Yasutaka Michiura, Takayuki Hirose, Miki Sasaki, Sayaka Ishizawa, Takashi Fukui, Yukako Ishitsuka, Yasuo Itabashi, Hiroharu Shibayama, Masaru Wada

March 7, 2022

Best Paper Committee

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<u>Peer review comment from US specialists</u>

Identifying critical parameters is a critical step that is often overlooked in health management modeling.

Your method uses a FRAM model to identify the data that is likely to have a large effect on the system.

As long as this model is constructed well, **this will greatly reduce the data space and should result in much better AI/ML models and results.**

Japan Manned Space Systems Corporation

JAMSS

ひとと宇宙を結ぶインテグレータ

Thank you