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Sensitivity enhanced method for fault detection and prediction of elevator doors using a margin maximized hyperspace

Minjae Kim*, Seho Son, and Ki-Yong Oh
*Presenter
Applied Dynamics and Intelligent Prognosis Laboratory
Department of Mechanical Convergence Engineering
Hanyang University

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1 Motivation & background

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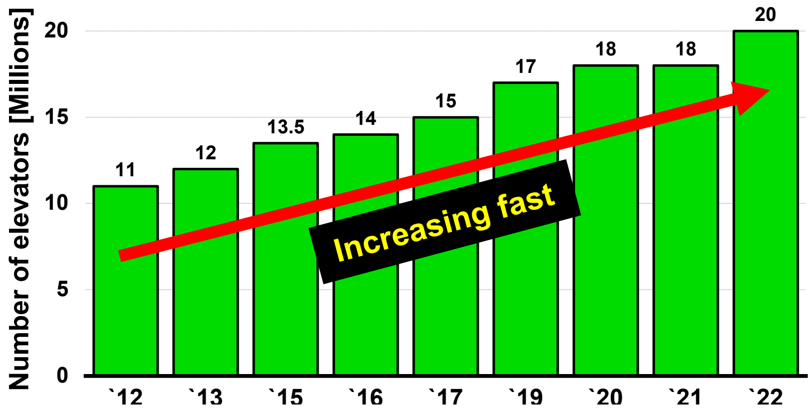
Increasing number of elevators in urban area



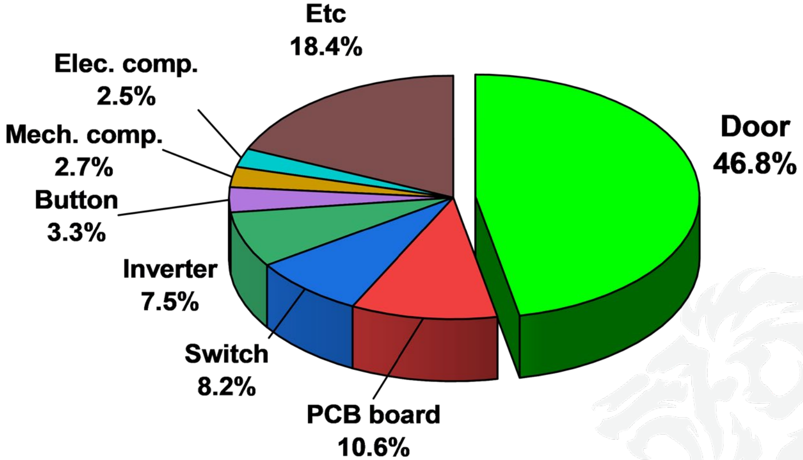
Number of elevators and escalators in operation

https://www.kone.com/en/Equity-story-2023

Apartments in Seoul

https://en.yna.co.kr/view/AEN20201202004000320

Necessity for effective elevator door fault detection and diagnosis (FDD) methods



Effective FDD methods for elevator doors are required

1 Motivation & background

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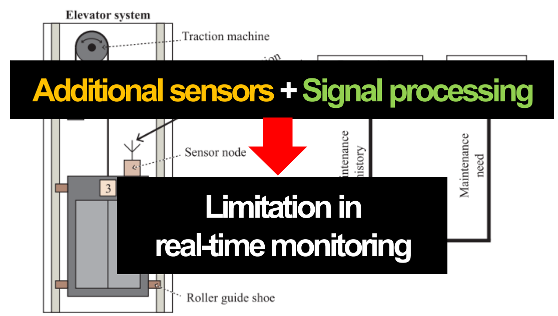
Existing FDD methods for solving elevator door FDD problems

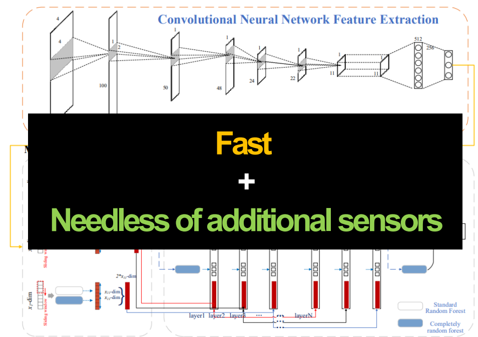
Complex structure of elevator
Liang et al. 18th CASE IEEE (2022)



Additional sensors + Signal processing

Limitation in real-time monitoring

Physical sensor-based methods
Skog et al. IEEE Sens. J. (2017)



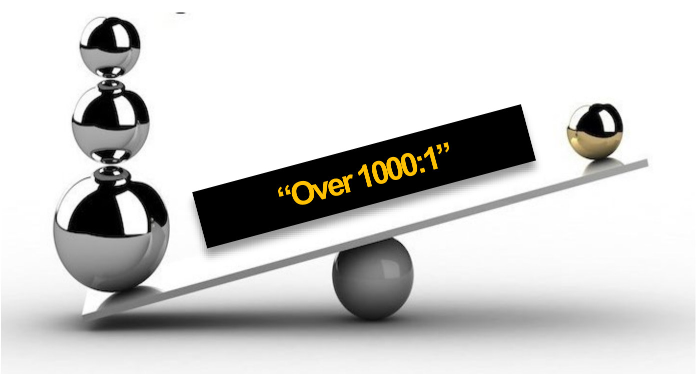
Fast
+
Needless of additional sensors

ML methods with operational data
Zhang et al. 27th ICAC. IEEE, (2022)

Challenges for solving real-world FDD problems

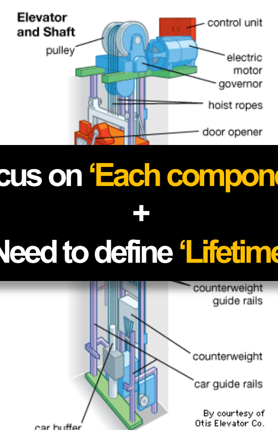
Normal

Faulty



"Over 1000:1"

Extremely imbalanced between



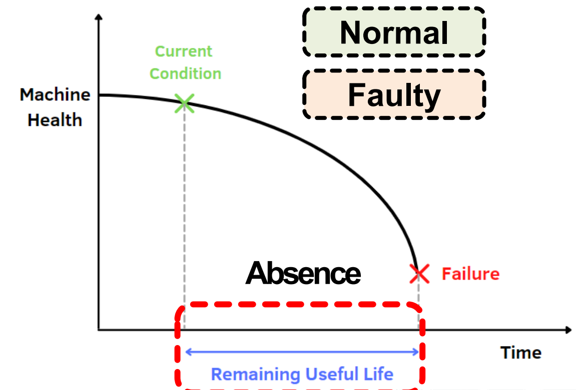
Focus on 'Each component'
+
Need to define 'Lifetime'

Impossible to define RUL

Only available

Normal

Faulty



Impossible to detect degrading sign on

Effective solution for real-world FDD problem is required

Motivation & background

Motivation

- **The number of elevators** in urban area containing lots of buildings is **increasing fast**
- The **elevator faults**, especially for **doors** frequently occur
- **Accurate** but **robust** FDD methods are required

Challenges

- Extreme **imbalance** between **normal** and scarce **fault data**
- Impossible to define RUL of the complex system
- Impossible to detect degrading sign on binary dataset only containing normal and faulty data

Research goal

- Develop **accurate FDD method** for solving highly imbalanced real-world dataset
- **Define RUL** focusing on **each component** instead of the entire system
- **Predict faults** even in the absence of degrading data

Overall framework

Phase A. Preprocessing

A.1. Data separation

- Method : Using boolean signal
- Process : Divide each data based on their health condition

A.2. Data interpolation

- Method : Linear and nearest interpolation
- Process : Skip data except gathered with 8~10Hz and interpolate into 10Hz

A.3. Statistic feature extraction

- Method : Peak, mean, RMS
- Process : Extract statistic features and use the data instead raw data to decrease learning difficulty

Phase B. Model construction

B.1. High-level feature extraction

- Method : VAE
- Process : Compress input data into 2D latent space using VAE

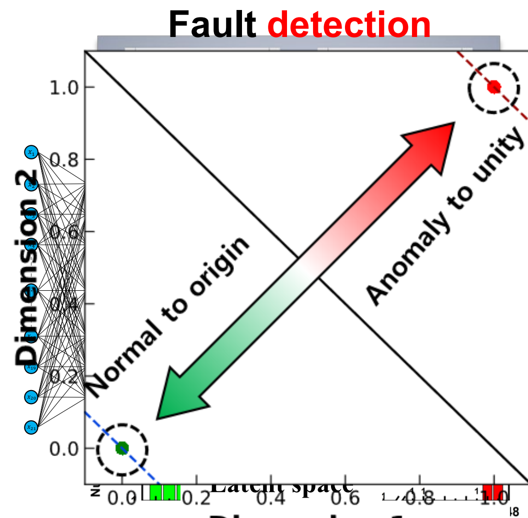
B.2. Model optimization

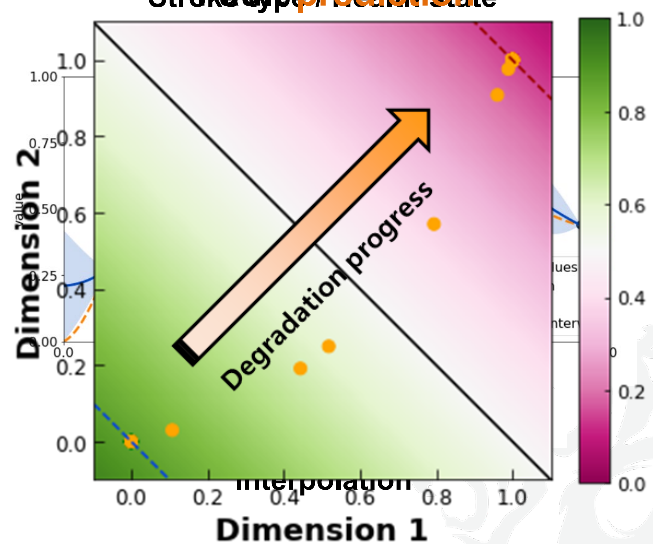
- Method : Bayesian optimization
- Process : Converge the VAE model and find the MMH

Phase C. Application

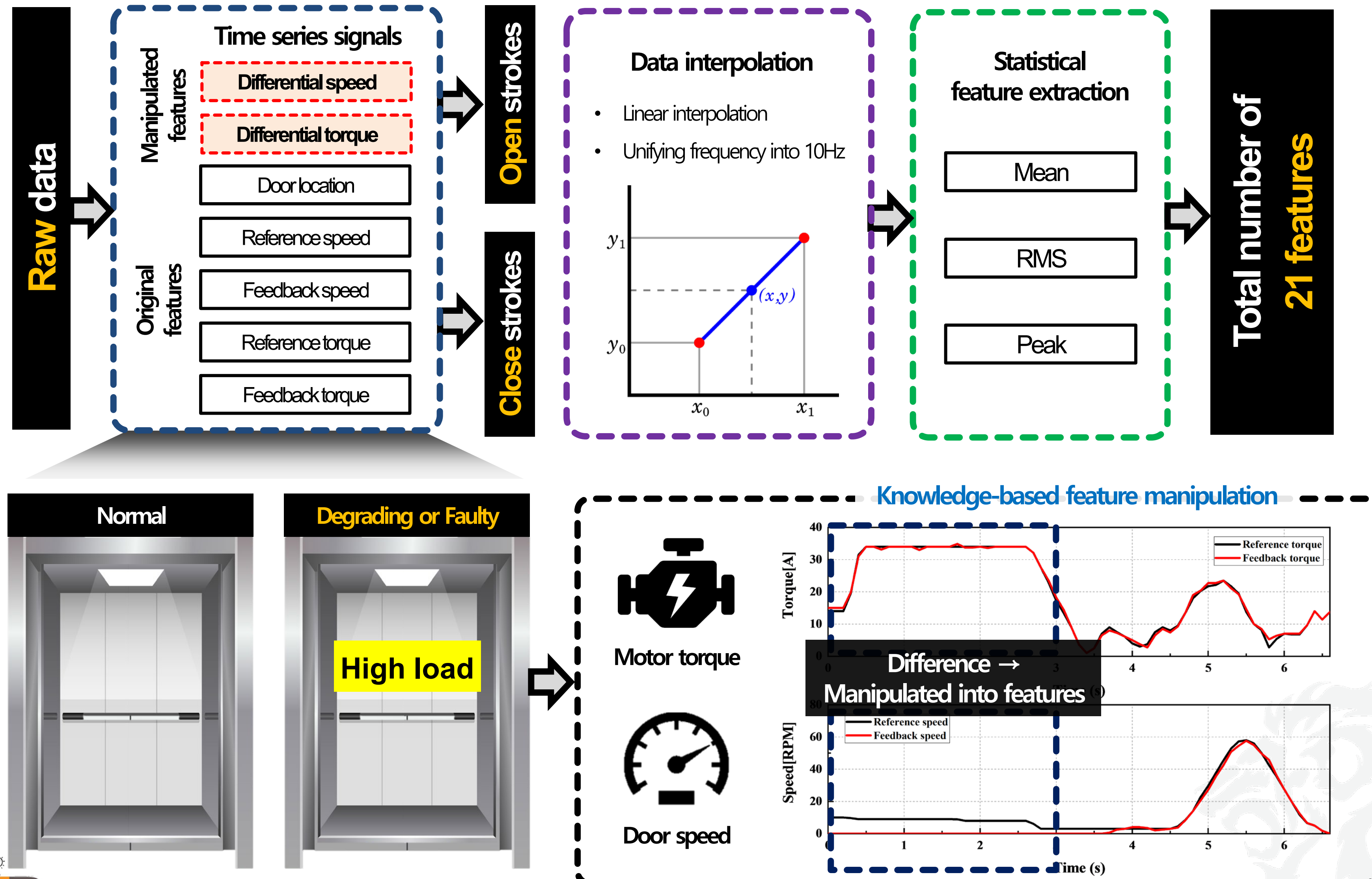
Fault Detection & Prediction

- Method : SVM
- Process : Classify current states and predict RUL based on marginal distance





Phase A. Preprocessing



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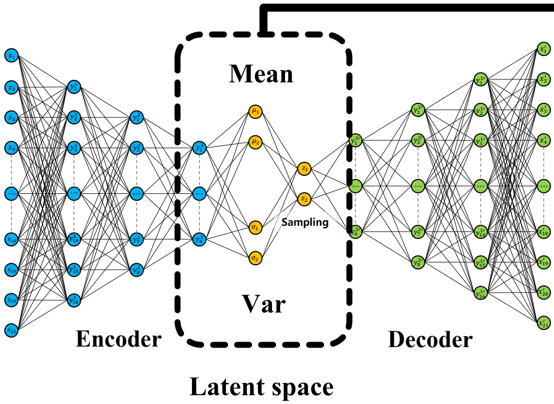
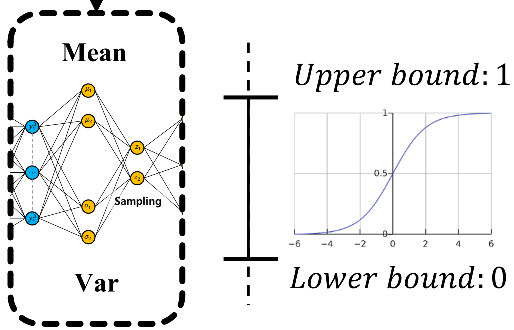
Phase B. Model construction

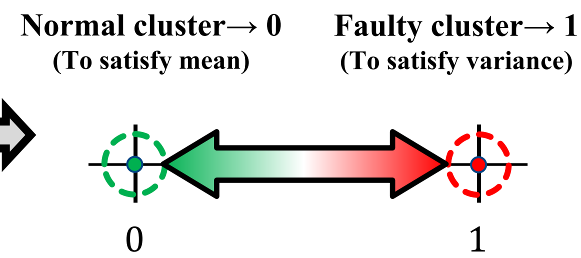
➢ Margin Maximized Hyperspace (MMH)



Variational Auto Encoder (VAE)

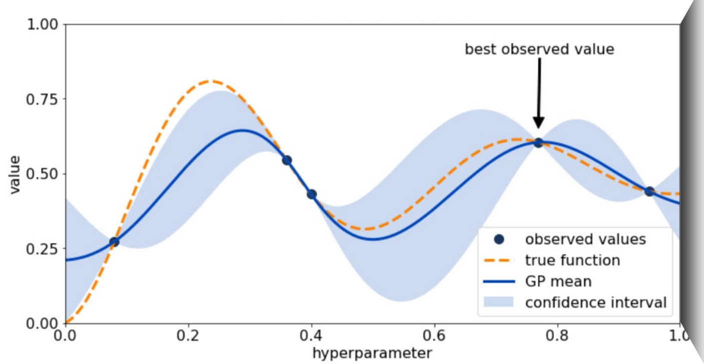


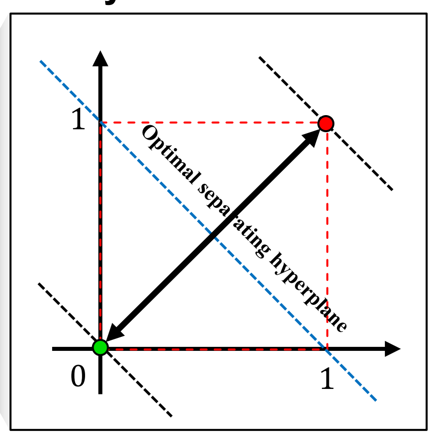
Regulate latent space

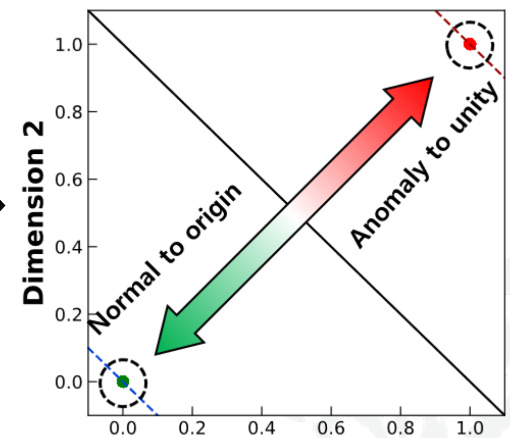


Separate normal/faulty cluster

➢ Bayesian Optimization for enhanced stability



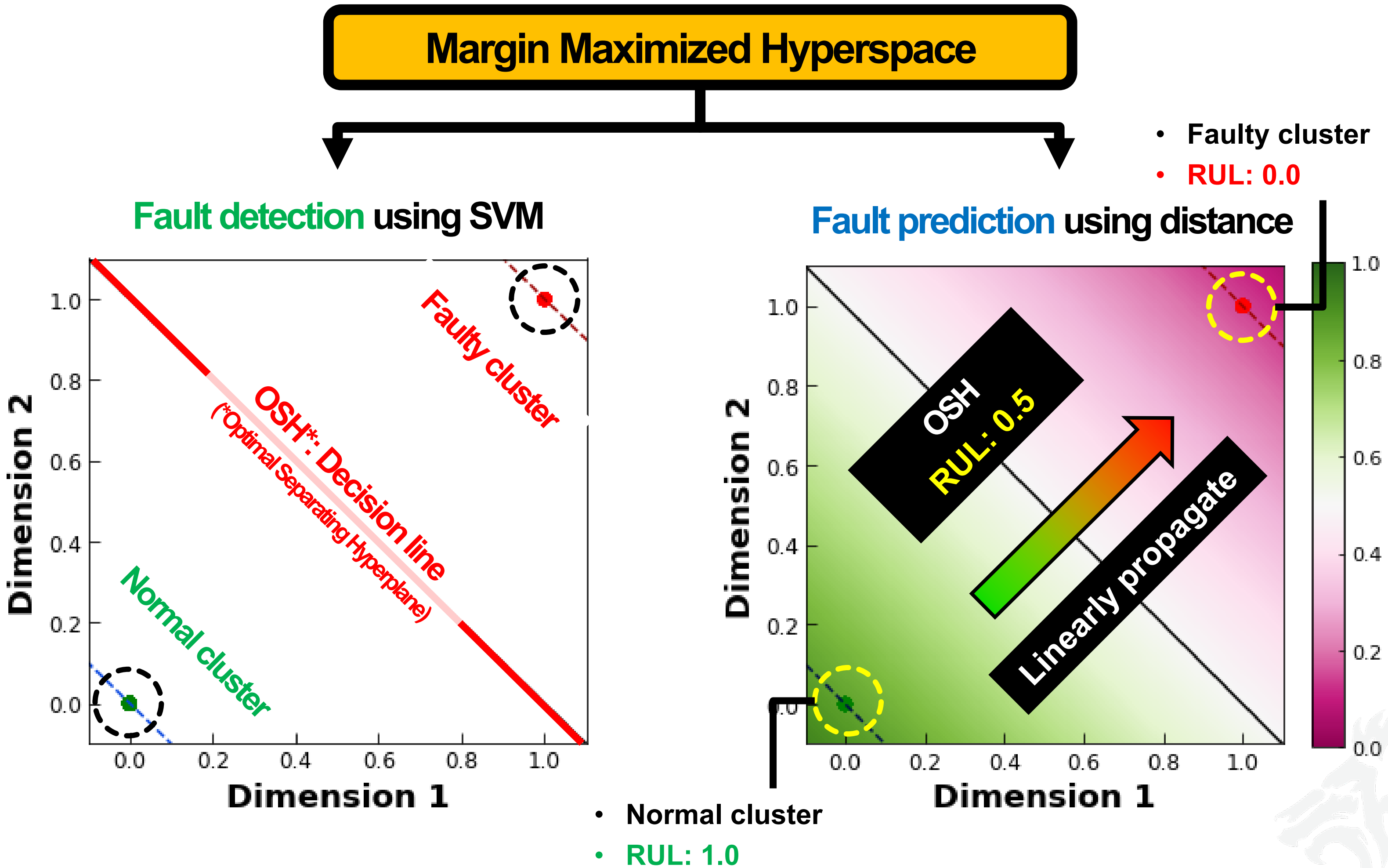




Maximize sensitivity separating normal and faulty clusters with VAE

Phase C. Application of MMH

- Fault detection and prediction using MMH



Application of MMH for fault detection and prediction

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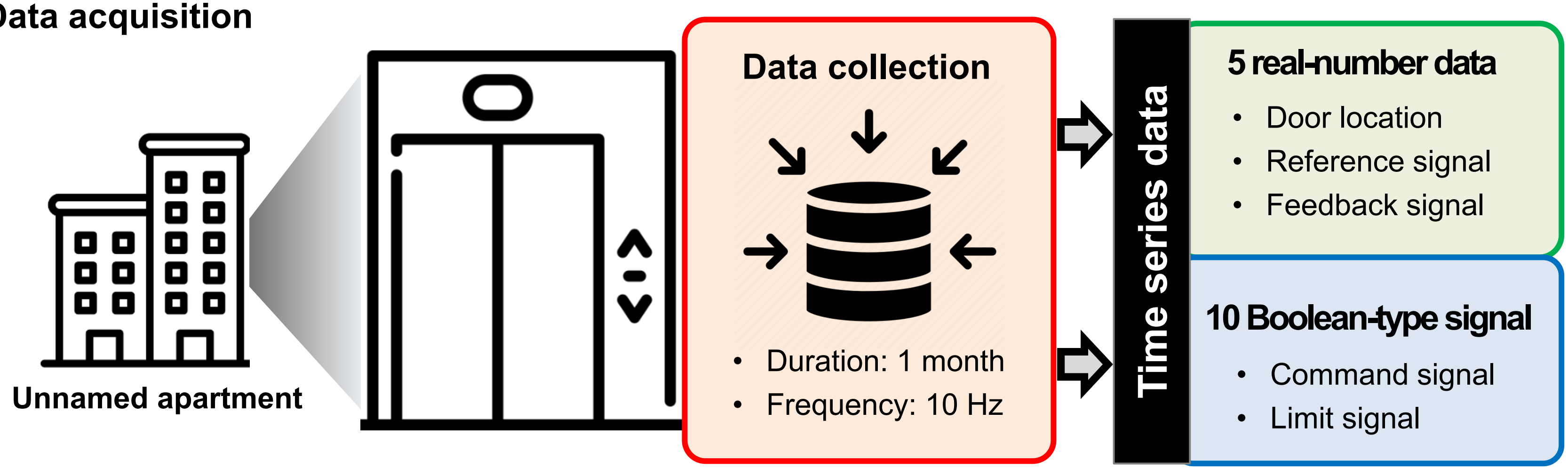
Elevator door operating dataset

- **Data acquisition**



- **List of features used for training and testing**

Feature number	Feature name
1-3	Door location (Peak, mean, RMS)
4-6	Reference speed (Peak, mean, RMS)
7-9	Feedback speed (Peak, mean, RMS)
10-12	[illegible] mean, RMS)
13-15	Reference torque (Peak, mean, RMS)
16-18	Feedback torque (Peak, mean, RMS)
19-21	Differential torque (Peak, mean, RMS)

21 features in total

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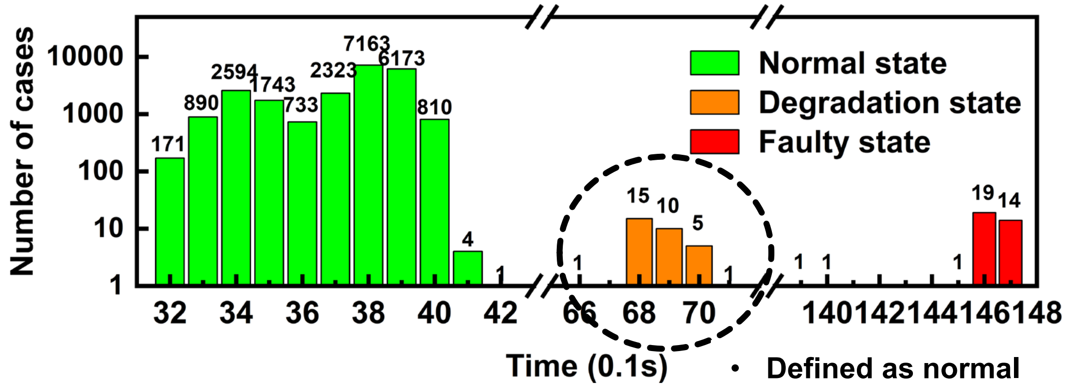
Elevator door operating dataset

➢ Time dependency of elevator door motor health state

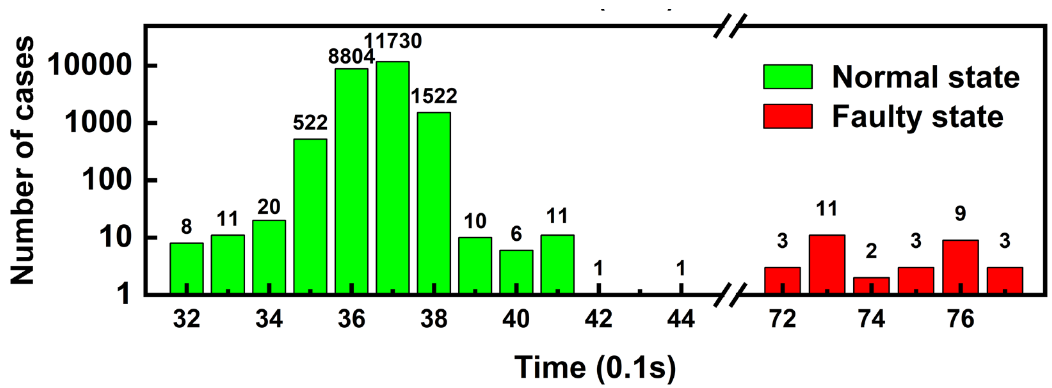
❖ Open strokes



Health state	Number of strokes
Normal	22605
Degradation	32
Faulty	36
Total	22673

- Defined as normal
- Demonstrates time delay and huge load

❖ Close strokes

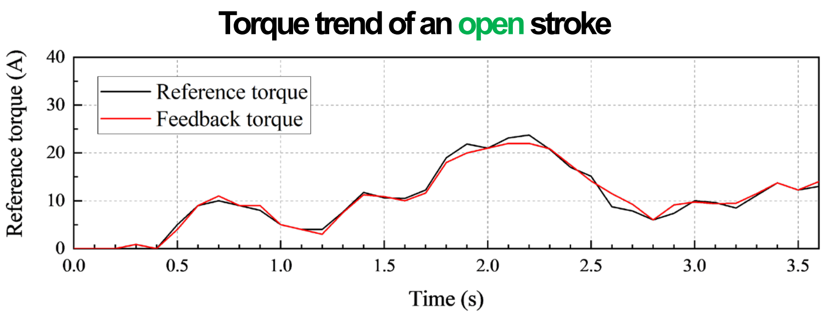


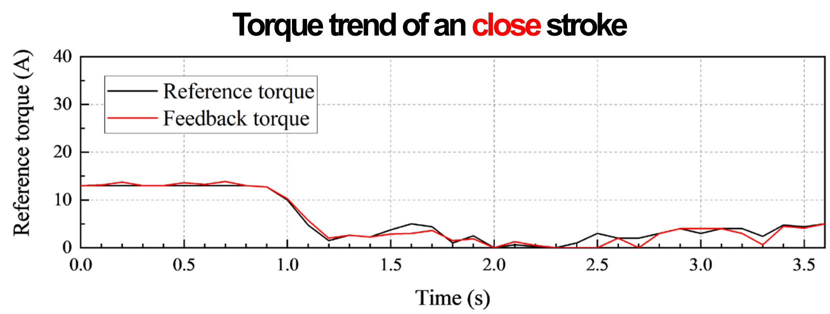
Health state	Number of strokes
Normal	22646
Degradation	0
Faulty	31
Total	22677

ADIP

Reason for selecting open strokes for validation

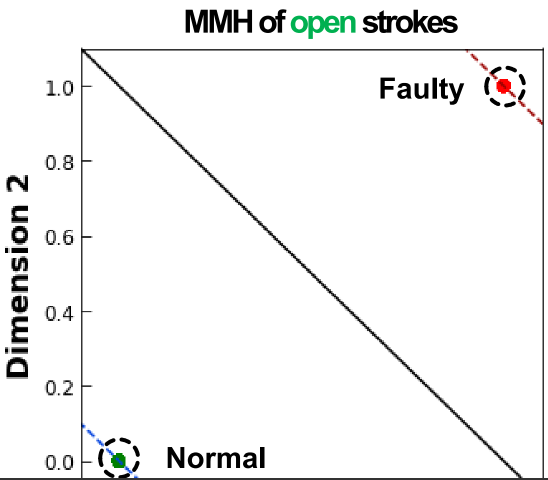
➢ Clear indicator of door motor failure

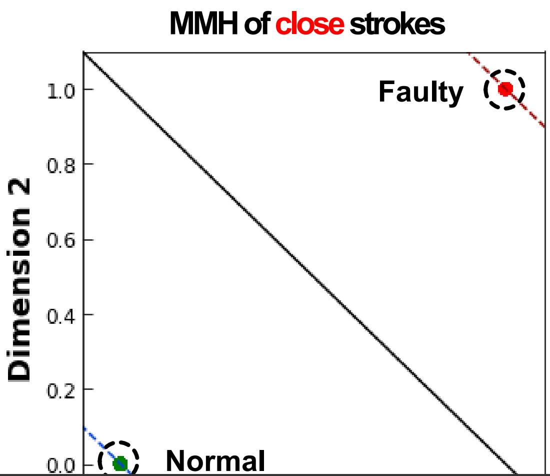


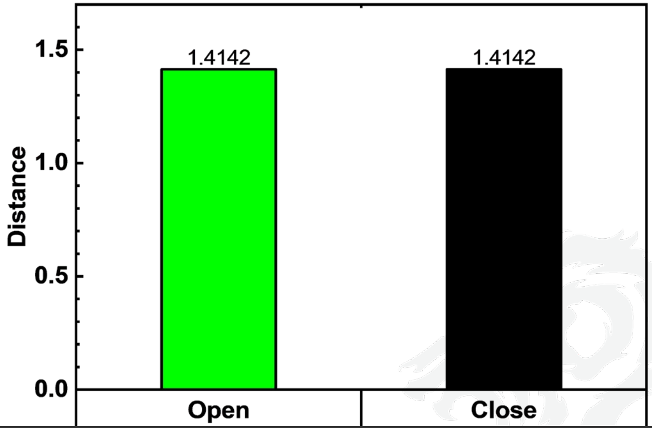


- Safety issue → Purely opened by motor **torque**, mostly closed by **inertia**
- Health state of door motor → Less clear in close strokes **(Degrading strokes X)**

➢ Redundancy for discussing both strokes





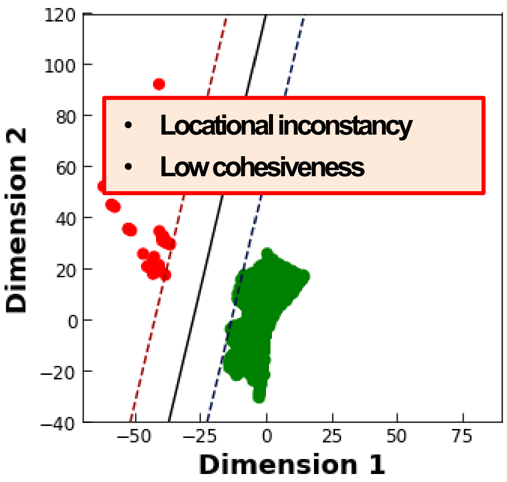


Only used open stroke dataset for validation

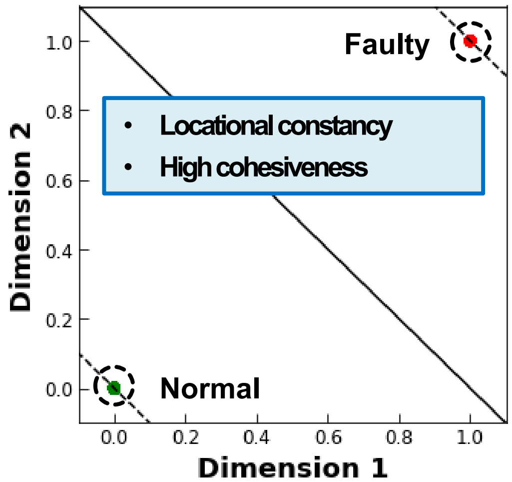
Result & Discussion

Effect of the latent space regulation

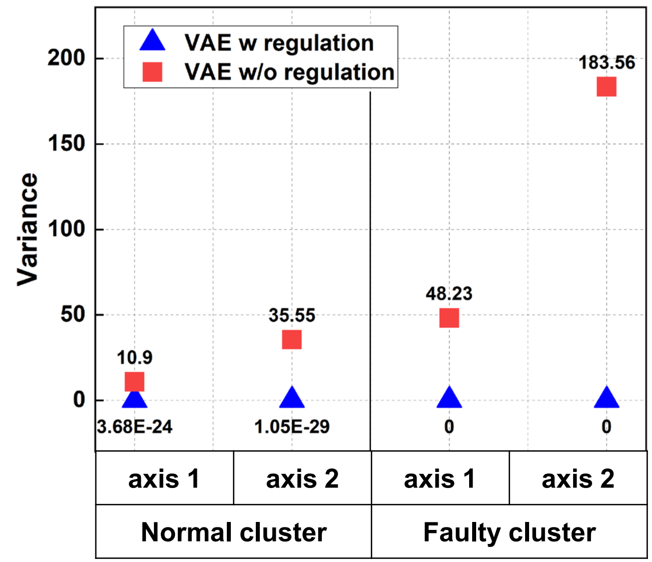
VAE w/o regulation



VAE w. regulation

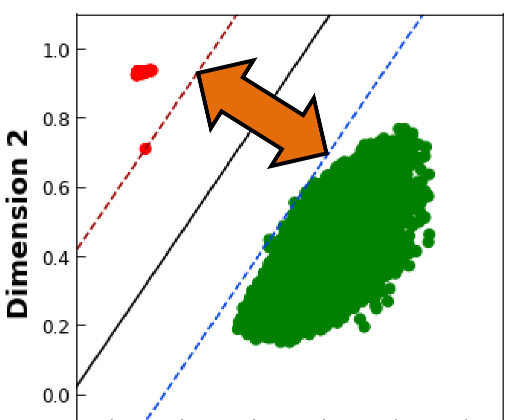


Variance of normal/faulty clusters

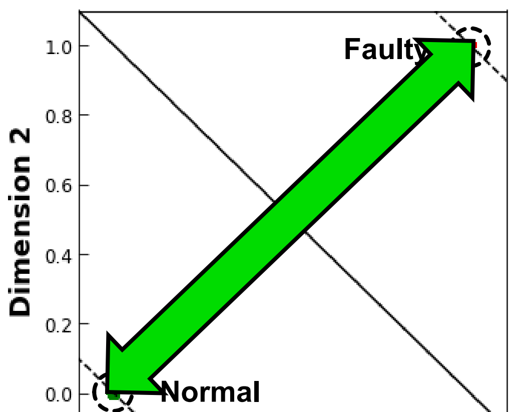


Comparison with other types of autoencoders

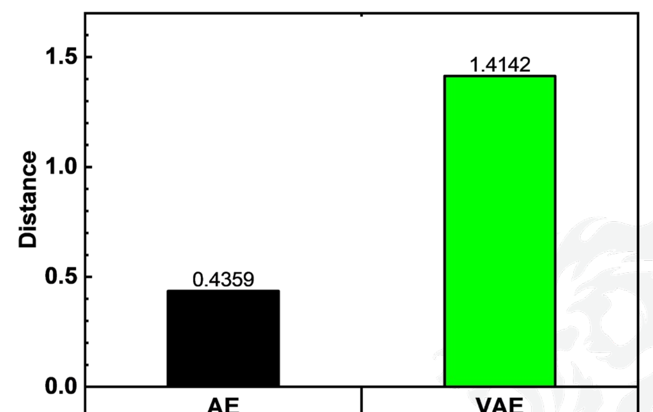
AE w. regulation



VAE w. regulation



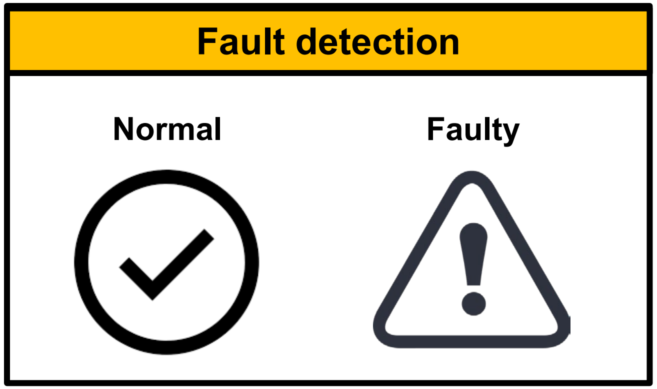
Distance between normal/faulty clusters



Demonstrates locational constancy and high cohesiveness

4 Result & Discussion

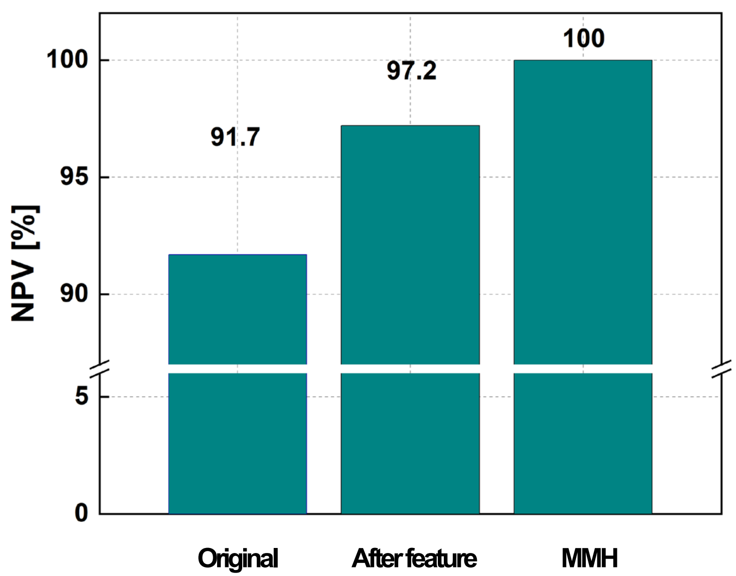
Validation for fault detection



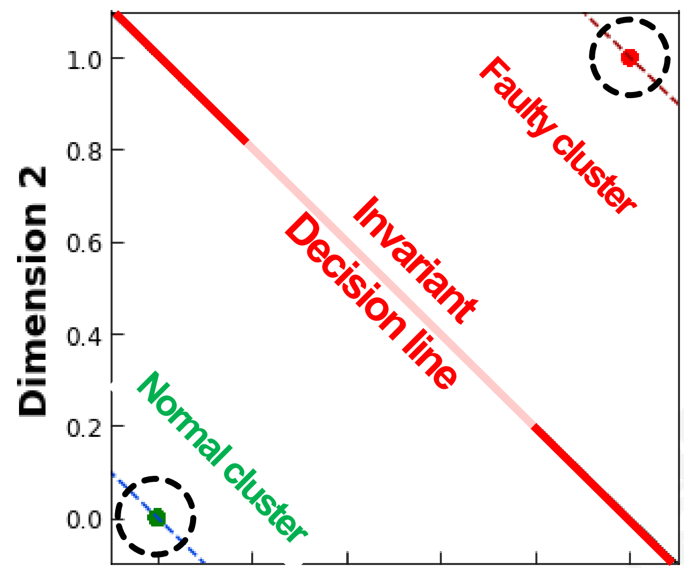
		Predicted	
		Positive	Negative
Actual	Positive	True positive (TP)	False negative (FN)
	Negative	False positive (FP)	True negative (TN)

$$NPV(Negative\ Predicted\ Value) = \frac{TN}{TN + FN}$$

NPV comparison



Invariant decision line of MMH

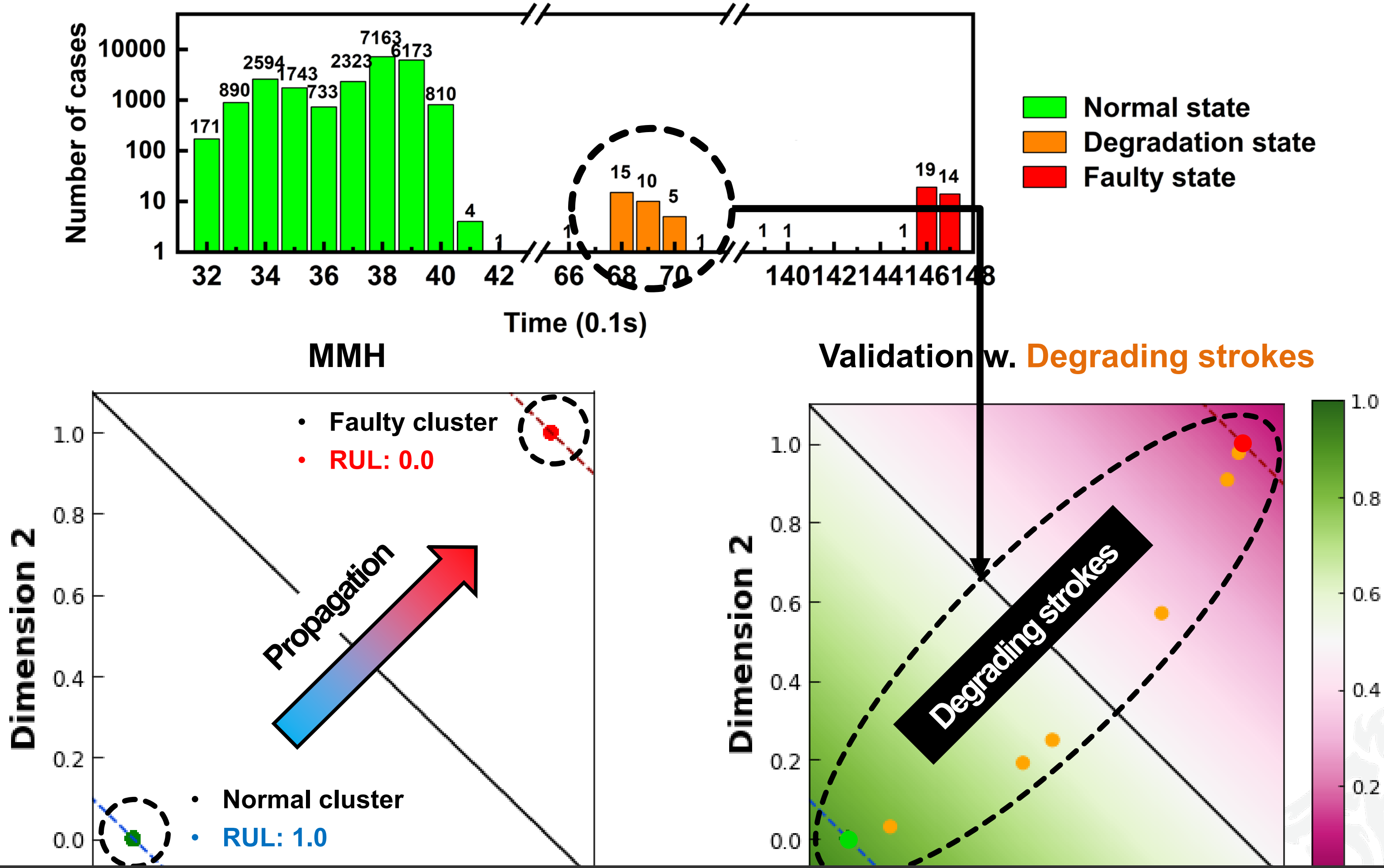


Demonstrates high accuracy for fault detection

Result & Discussion

Validation for fault prediction

- Fault prediction using degrading strokes



Effective for fault prediction under absence of degrading data

Conclusion & Future work

Conclusion

- **MMH (Margin-Maximized Hyperspace)** method is effective at detecting and predicting faults in highly-imbalanced dataset
- This method **maximizes sensitivity** separating two imbalanced clusters and shows locational constancy at latent space
- **Knowledge-based feature manipulation** improves accuracy, so that the method is effective at detecting faults
- **Distance-based RUL estimator** effectively detect potential faults and can quantitively predict RULs even without degrading data

Future work

- **Validation** of the method with elevators at other locations
- **Embed** the method for real-time FDD of operating elevators

Thank you