Abnormal State Detection Model Using Deep One-Class Classification in Nuclear Power Plant

2022.05.19

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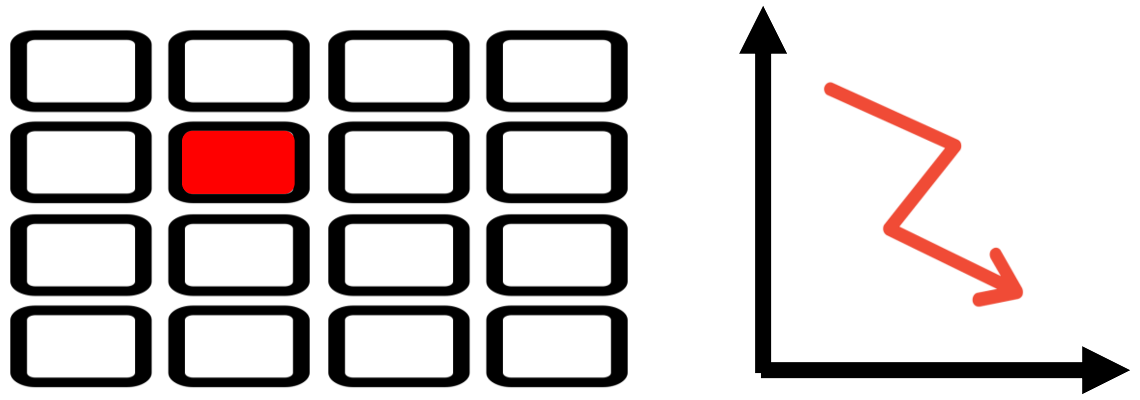
Introduction

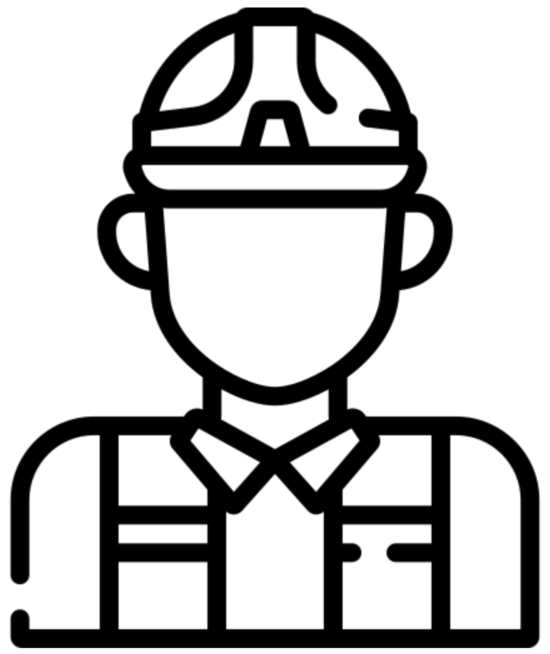
Alarms and plant parameters

Alarms

CC-PP01A
HDR Dsch Pres



Recognition



Diagnosis

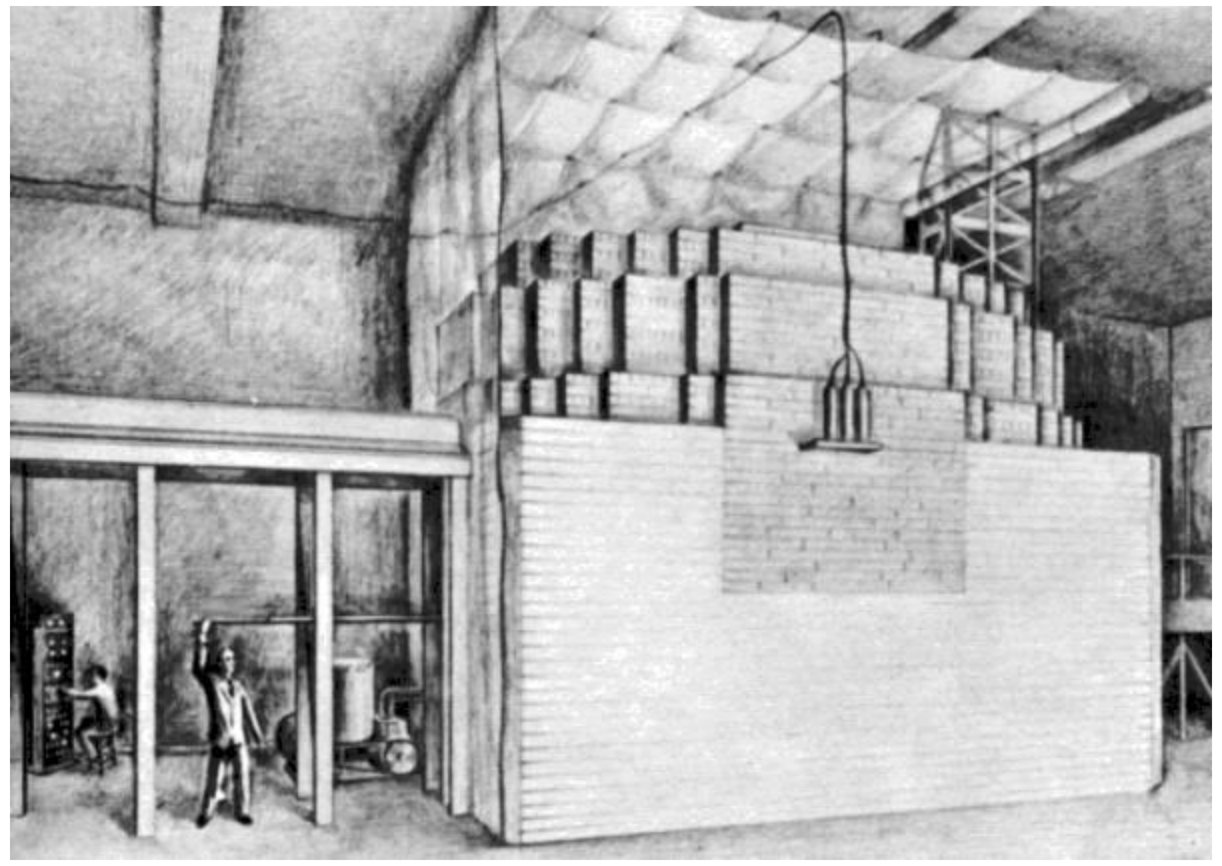
Abnormal operating procedures

CCW abnormal state

CCW pump trip
CCW service loop header leak
…
...

Misdiagnosis or late execution
= Human error

Reactor trip



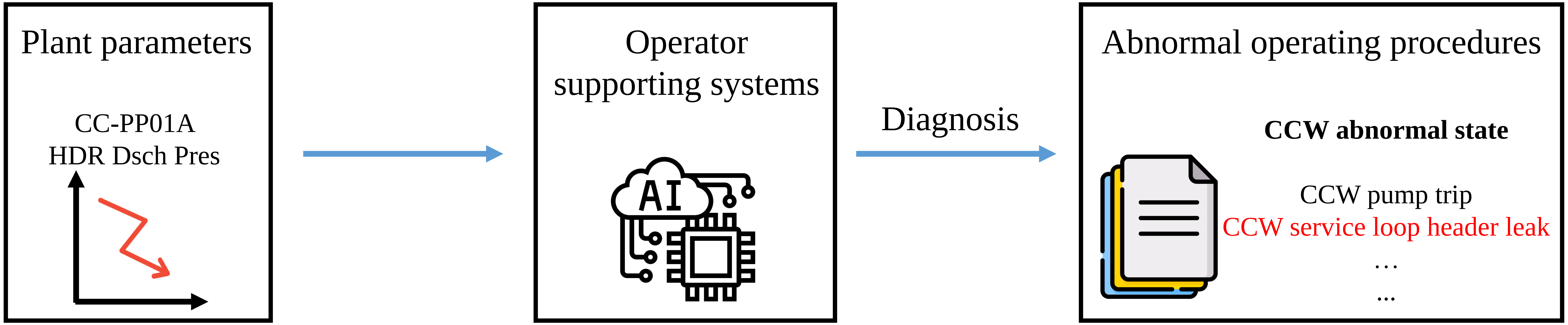
Introduction

- There are hundreds of alarms and thousands of plant parameters in a nuclear power plant (NPP)

- Operators must diagnose a proper abnormal operating procedure (AOP) in limited time
  - ✓ There are 82 AOPs for advanced power reactor 1400 (APR-1400) with 224 sub-procedures

- **These problems make operator confused and lead to reactor trip due to human error**

- **To reduce human error and increase safety of NPPs, operator supporting systems have been researched using artificial intelligence (AI)**



Introduction

- ❖ Most researches of abnormal states using AI focused on solving diagnosis problems

- ❖ However, too many types of abnormal states make abnormal state diagnosis models hard and it is difficult to apply in all cases due to problems of obtaining quality data

- ❖ Therefore, in reality, the research to detect abnormal states using only normal state data should be preceded

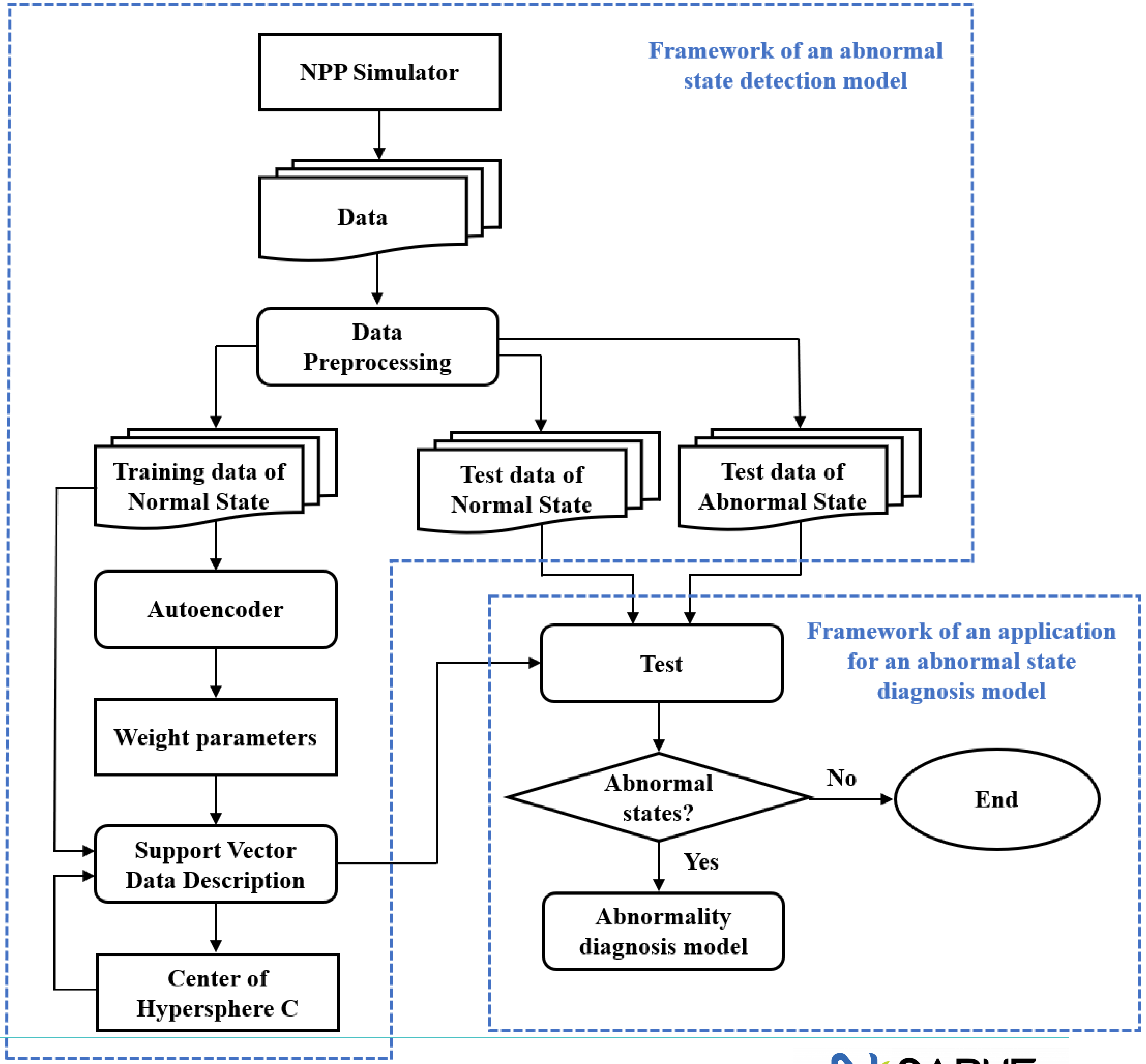
Objective

❖ **This research aims to develop an abnormal state detection model using a deep one-class classifier**
   ✓ Deep support vector data description (Deep SVDD) is used as a deep one-class classifier

❖ Since this model trains only normal state data, it is free to produce quality data and can be applied to most abnormal states

❖ **As a result, this abnormal state detection model contributes to reducing human error of operators in abnormal states by secure execution time**

❖ **Furthermore, this research can be a step to increase accuracy of an abnormal diagnosis model**

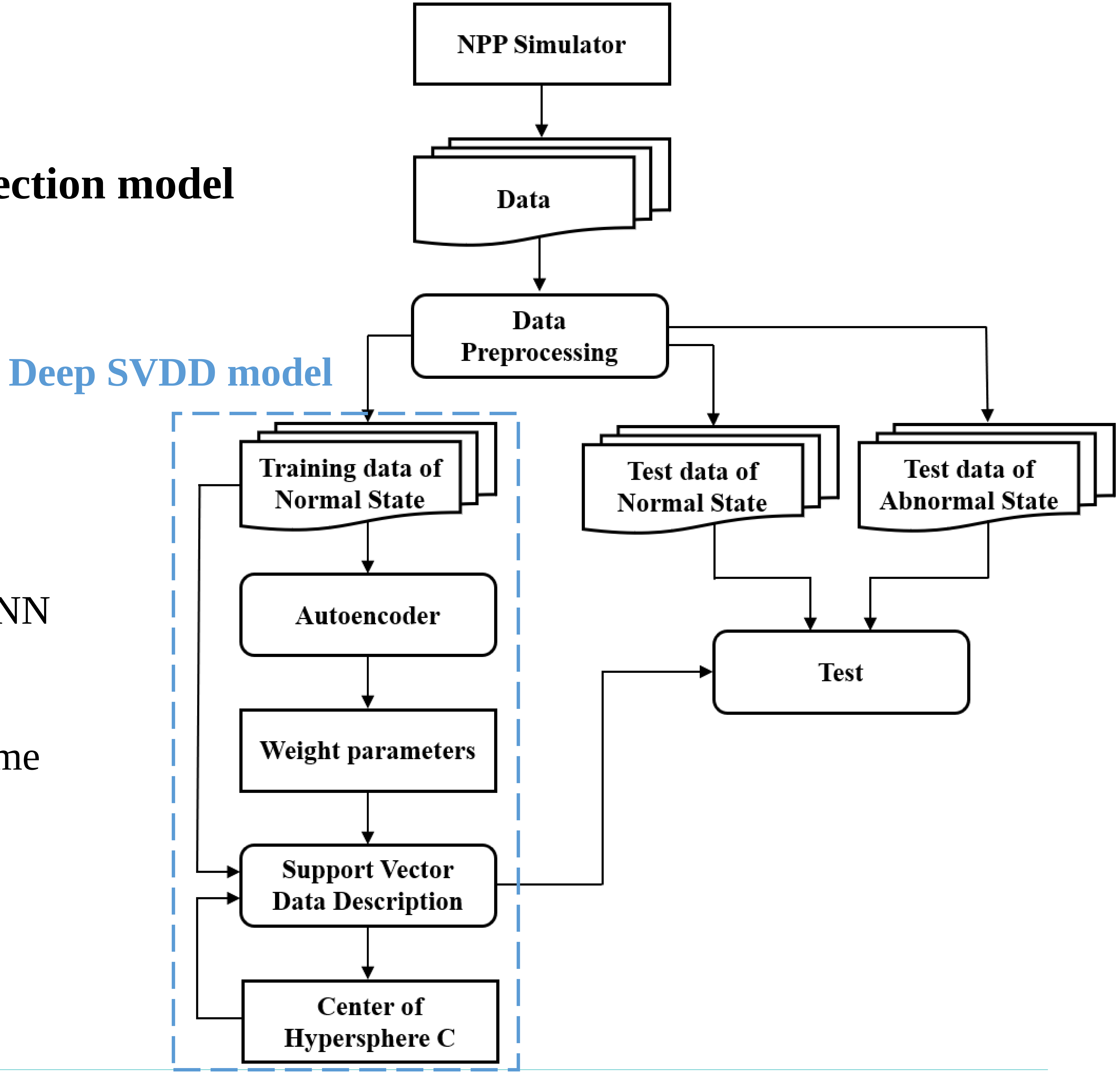


Methodology

An overall framework of the abnormal state detection model

❖ Three steps of the abnormal state detection model

- Data production and preprocessing
  - Data production by an NPP simulator
  - Data extracting and normalizing
- Deep SVDD model training
  - Training autoencoder and SVDD based on 2D-CNN
- Data test
  - Comparison between alarm time and detection time



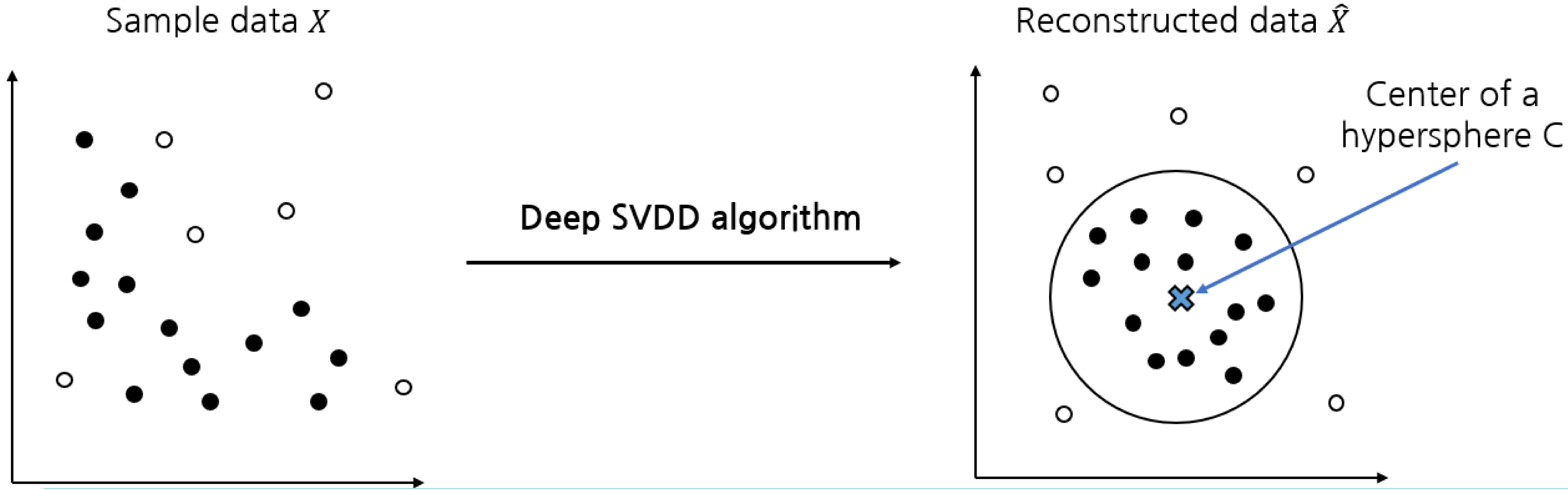
Methodology

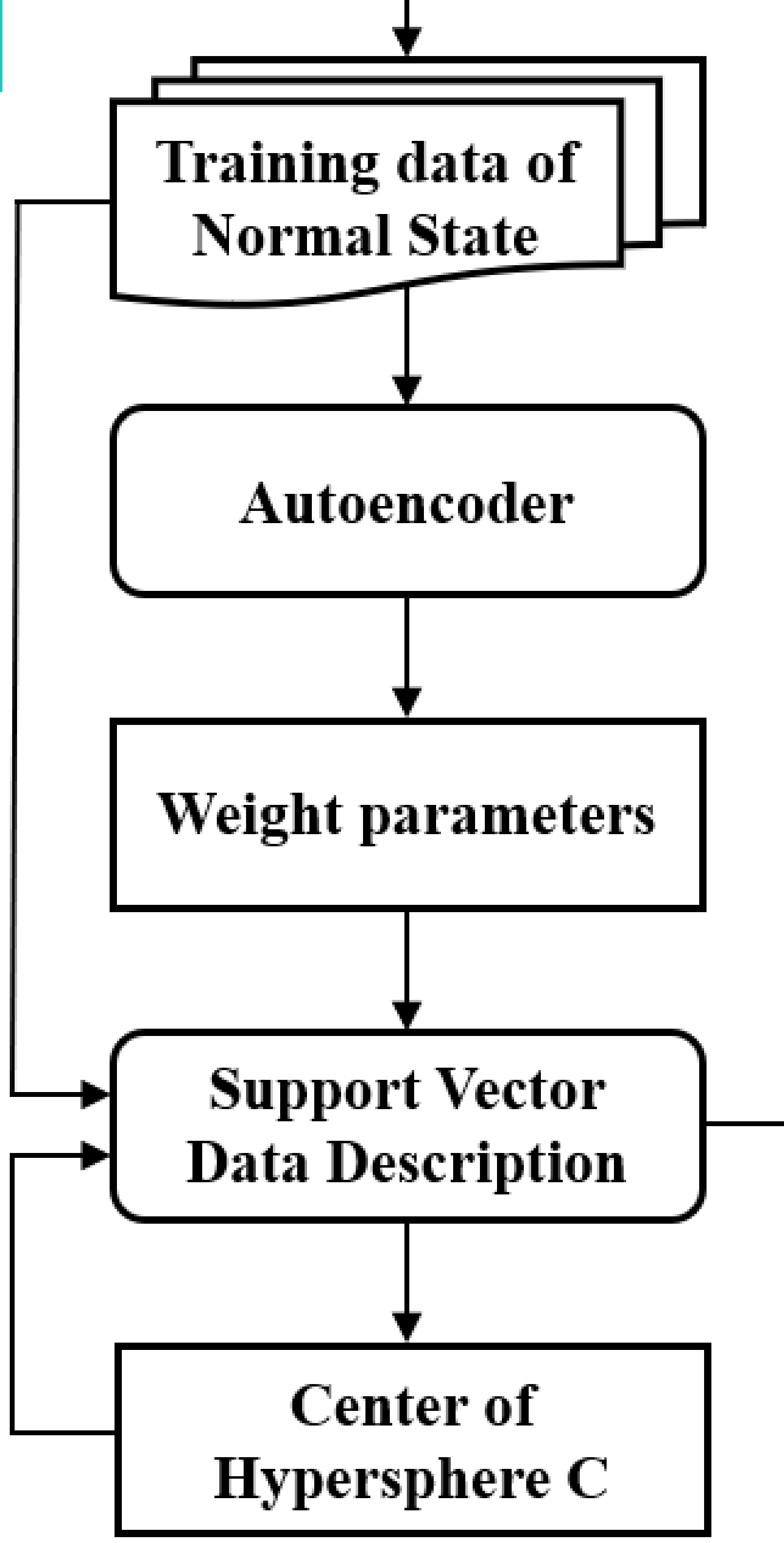
Deep SVDD description

- ❖ Unsupervised one-class classifier
- ❖ Derived model from one-class support vector machine

Aiming to find the center of a hypersphere C that enclosing normal data using neural networks

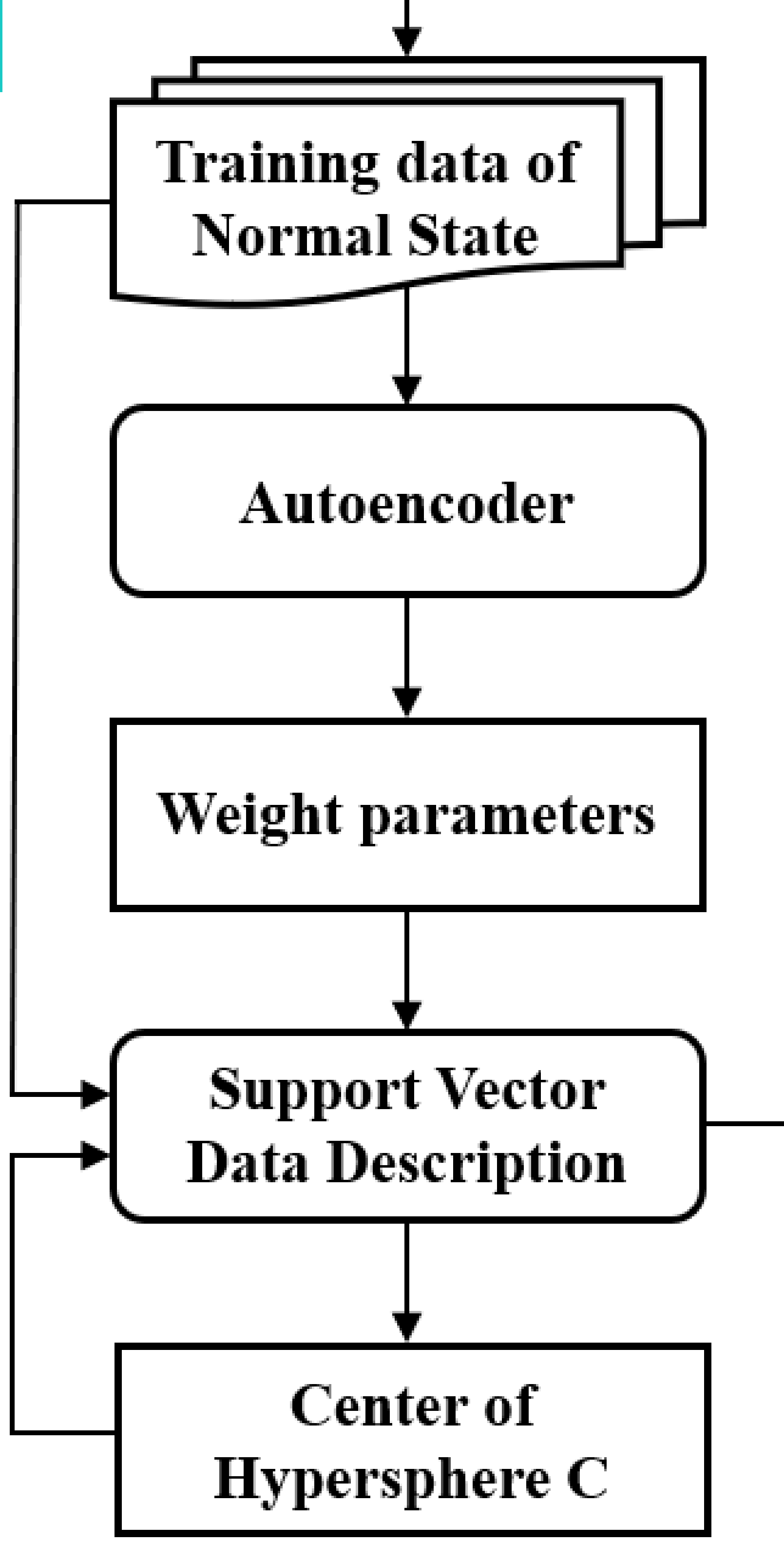
✓ Using autoencoder and SVDD based on 2D-CNN





Methodology

Objective and abnormal score function of Deep SVDD



❖ **Objective function**

$$\min_{W} \frac{1}{n}\sum_{i=1}^{n}\left|\left|\phi(x_i;W)-C\right|\right|^2+\frac{\lambda}{2}\sum_{l=1}^{L}\left|\left|W^l\right|\right|_F^2$$

- First term: Minimizing the distance between the center of a hypersphere C and the transformed normal data x by neural networks

- Second term: Optimizing weight parameters for extracting features of the normal data

❖ **Abnormal score function**

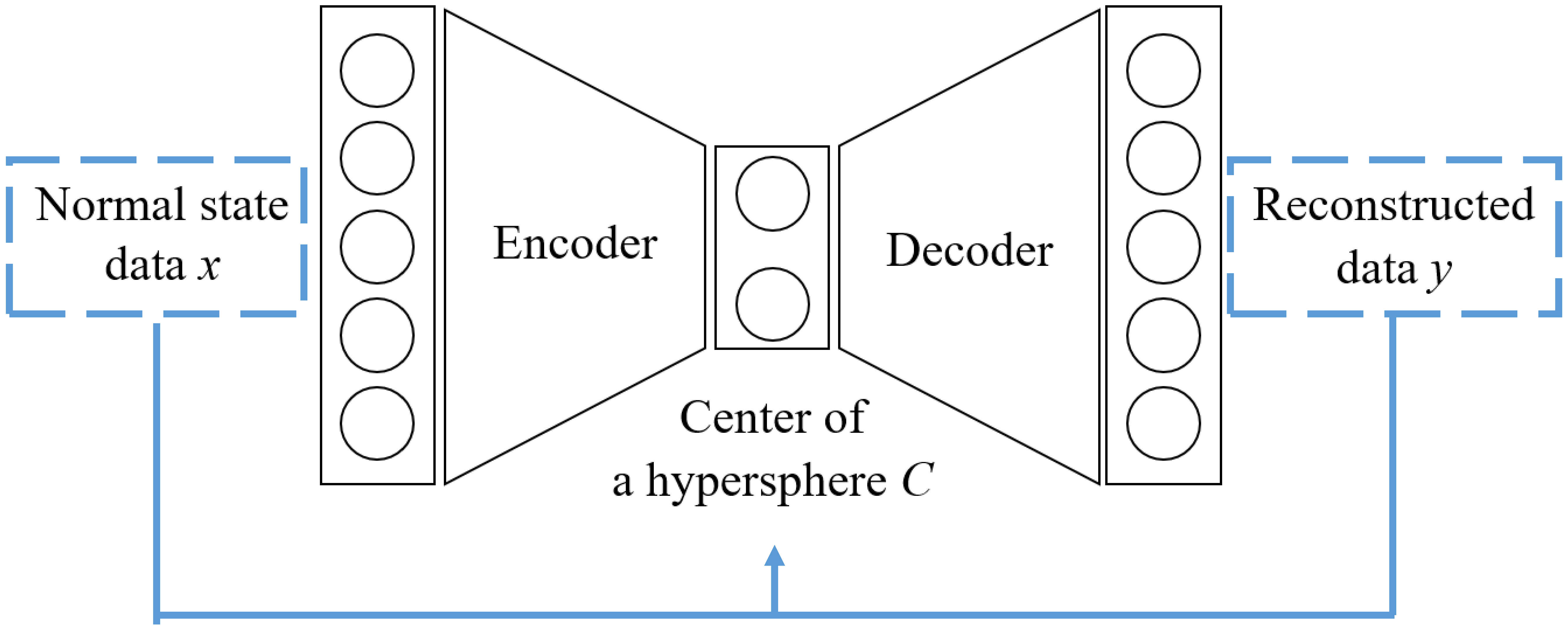
$$\boldsymbol{s(x)=\left|\left|\phi(x;W)-C\right|\right|^2}$$

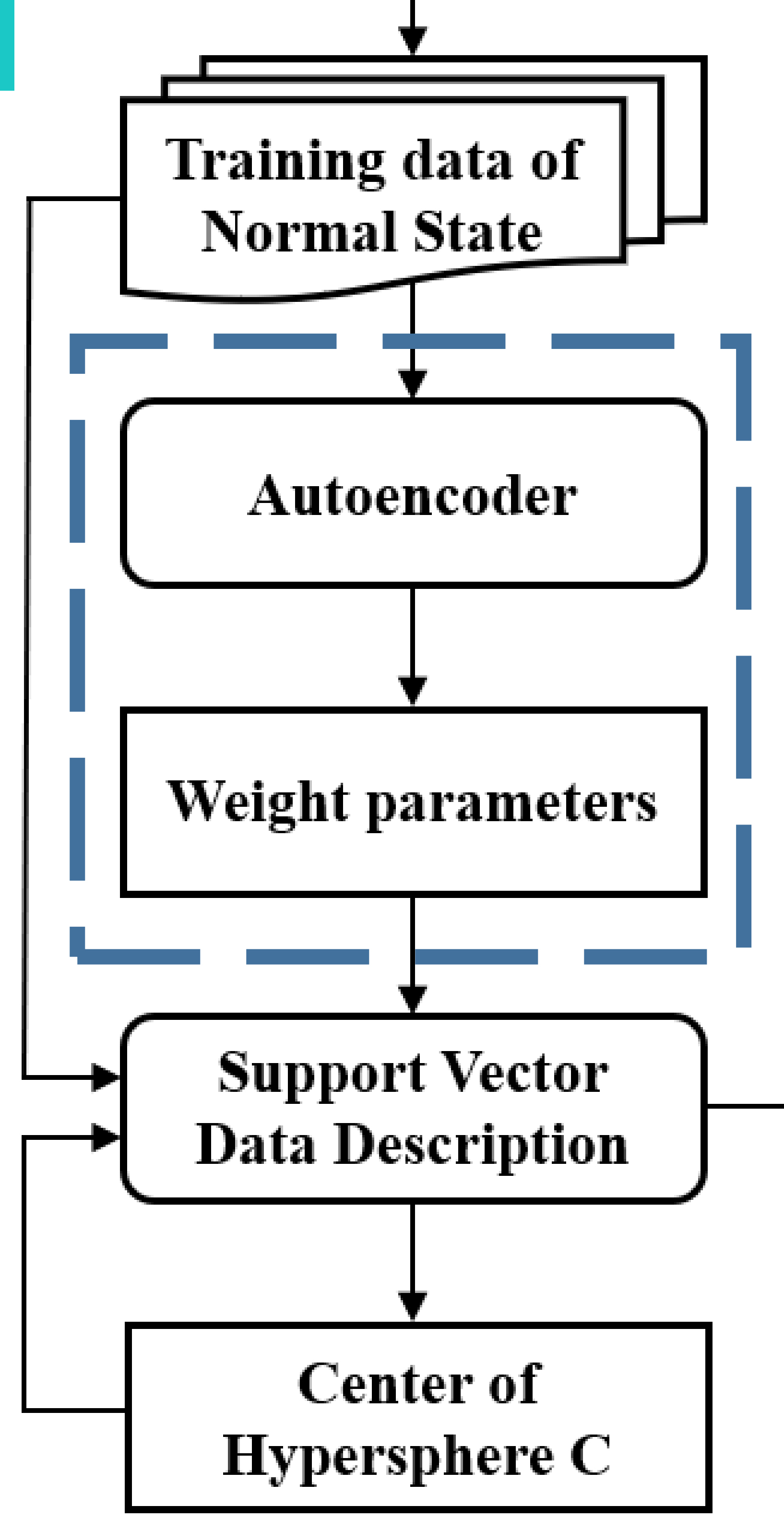
- Scoring through the distance between the center of hypersphere C and the transformed normal data x

Methodology

Optimizing weight parameters using autoencoder

- ❖ Reconstructed data y is generated by a 2D-CNN based autoencoder
- ❖ Weight parameters are calculated by reconstructed error of normal data x and reconstructed data y
- ❖ **The center of a hypersphere C is obtained by weight parameters**



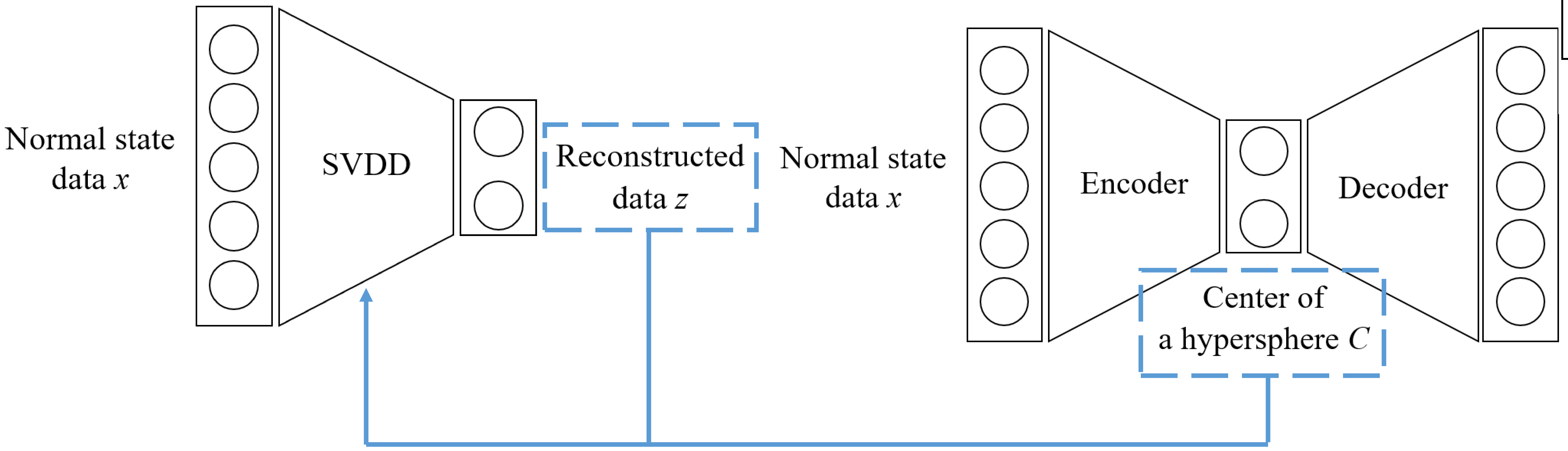


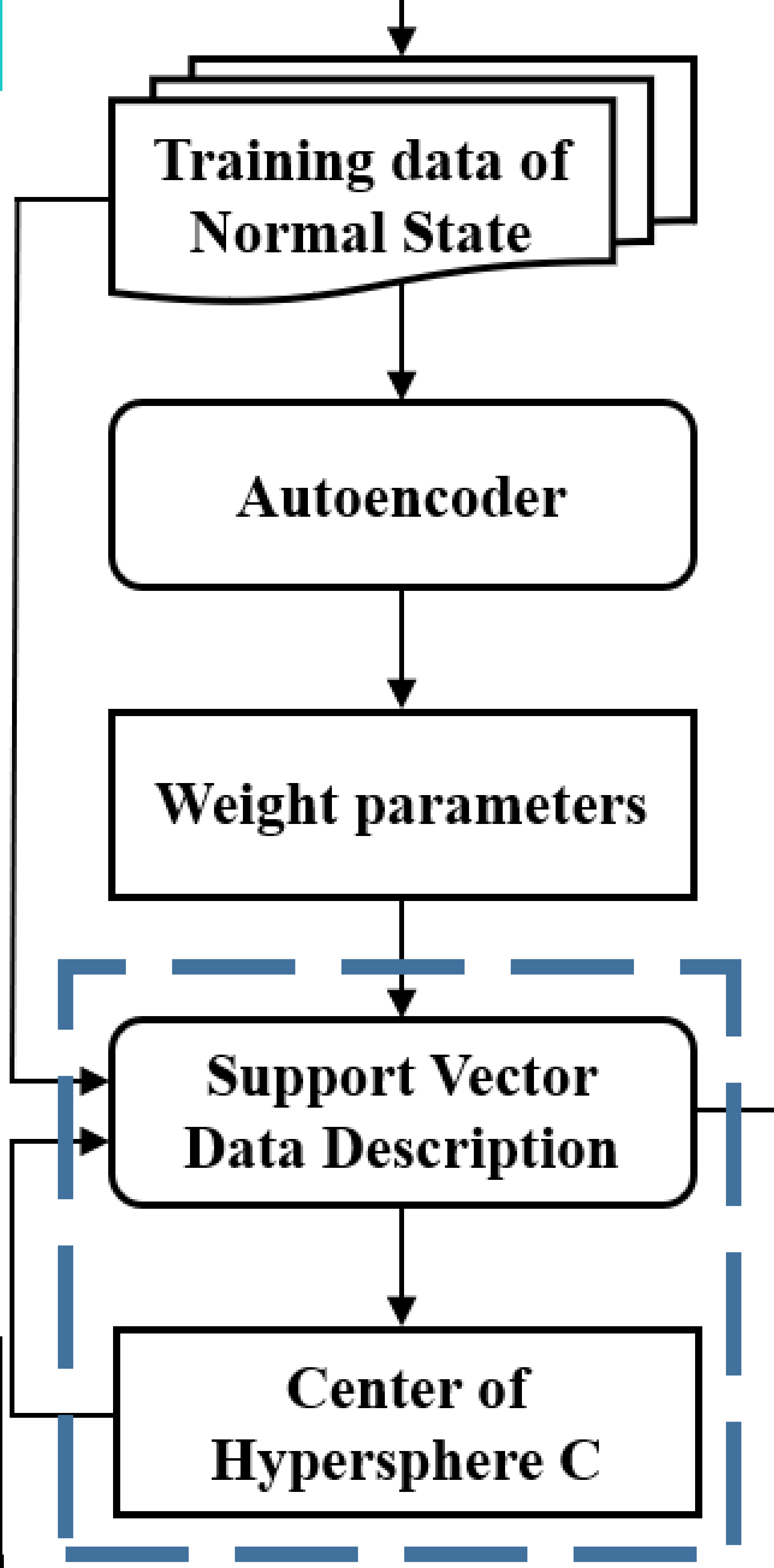
Methodology

Minimizing the distance using SVDD

- ❖ Reconstructed data z is generated by a SVDD with the same structure as the encoder part

- ❖ The SVDD model is trained by calculating the difference between the center of a hypersphere C and reconstructed data z

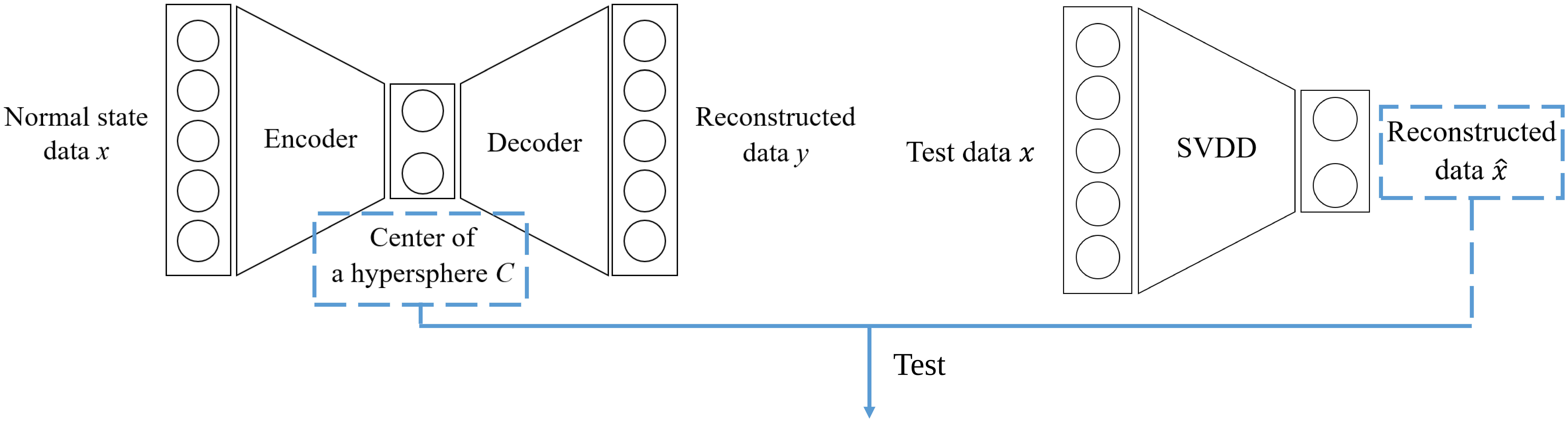




Methodology

Abnormal detection

- ❖ Reconstructed data z is generated by a SVDD with the same structure as the encoder part
- ❖ The SVDD model is trained by calculating the difference between the center of a hypersphere C and reconstructed data z

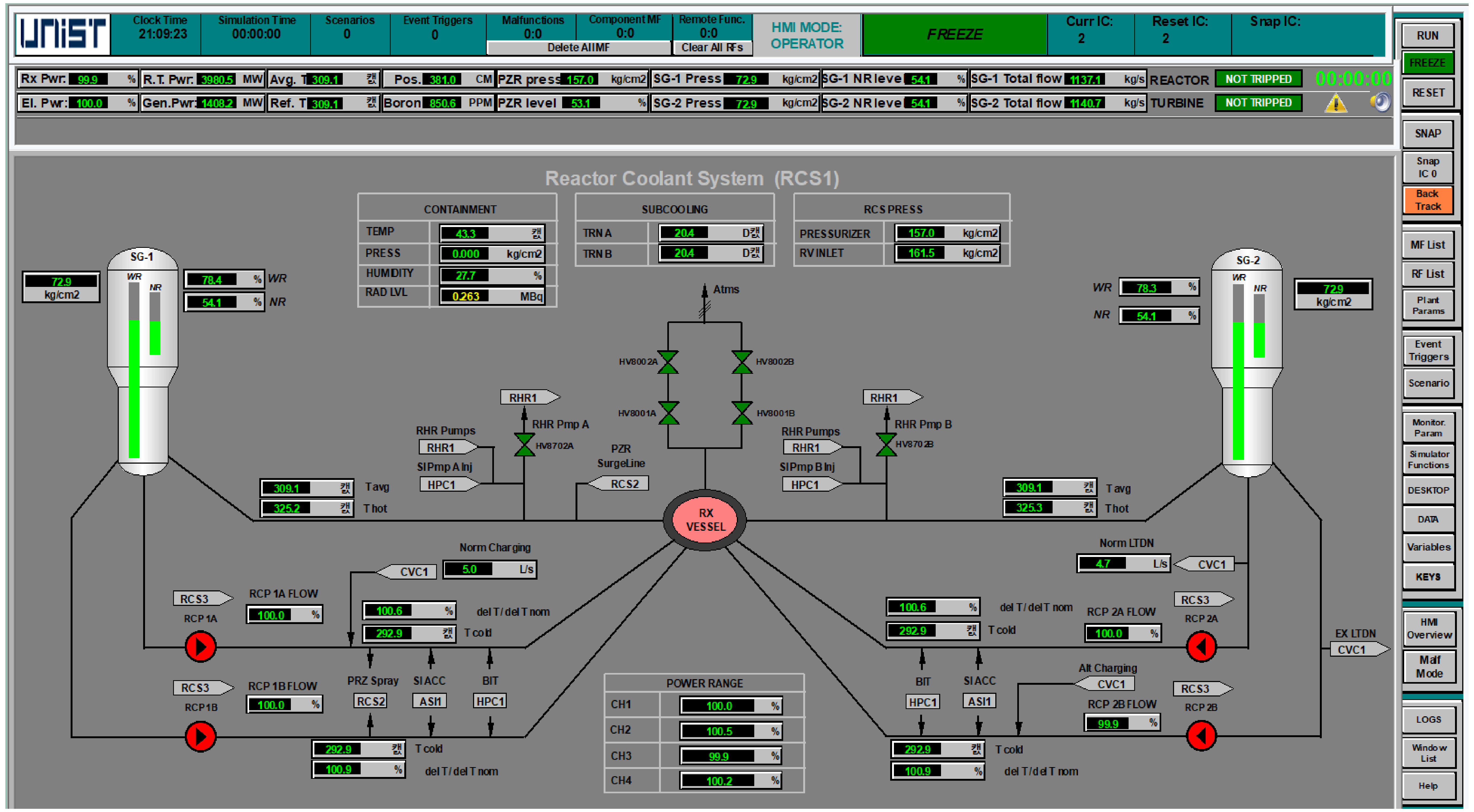


$$\boldsymbol{s(x) = ||\phi(x; W) - C||^2}$$

Case study

Data production

❖ 3KEYMASTER simulator
- 1400MWe 2-loop generic pressurized water reactor (PWR) simulator
- Made by western service corporation



Case study

Data production

- 2 labels
  - Normal state: label 0
  - Abnormal state consisting of 15 abnormal states: label 1

- Data shape of each data set
  - 60 seconds
  - 689 plant parameters

States	Description
Normal	Initial condition MOL 100%
SGTL	Steam generator A tube leak
CHRG	Charging line break upstream
LTDN	Letdown line leak inside containment
CDS	Loss of condenser vacuum
POSRV	Pilot operated safety relief valve leak
CWS	Circulating water tube leak in LP condenser
MSIV	Main stem isolation valve positioner failure
RCP	CCW service loop header leak to aux atm
MSS	Steam generator A steam line 1A break inside containment
PZR	Pressurizer spray valve positioner failure
CCW	CCW service loop header leak to aux atm
LFH	Feedwater heater 1A tube break
HFH	Feedwater heater 5A tube break
MFW	MFWP recirculating valve positioner open failure
TCS	High pressure turbine control valve positioner close failure

Case study

Data set description

- ❖ Number of data set
  - Normal state
    - 50 normal data set
    - 50 noise data set with 0.001 standard deviation
    - 50 offset data set with 1% offset
  - Abnormal state
    - 45 abnormal data set
- ❖ Train data set
  - 60% of normal data set
- ❖ Validation data set
  - 10% of normal data set
- ❖ Test data set
  - 30% of normal data set: 45 data set
  - All abnormal data set: 45 data set

States	Description
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Case study

Data preprocessing

- Normalization method is a squared minmax normalization.

- The minimum and maximum values are selected based on the normal state data
  - ✓ As a result, **plant parameters with abnormal state data has a large deviation**

$$\hat{x} = \left(\frac{x - x_{min,normal}}{x_{max,normal} - X_{min,normal}}\right)^2$$

Case study

Test method

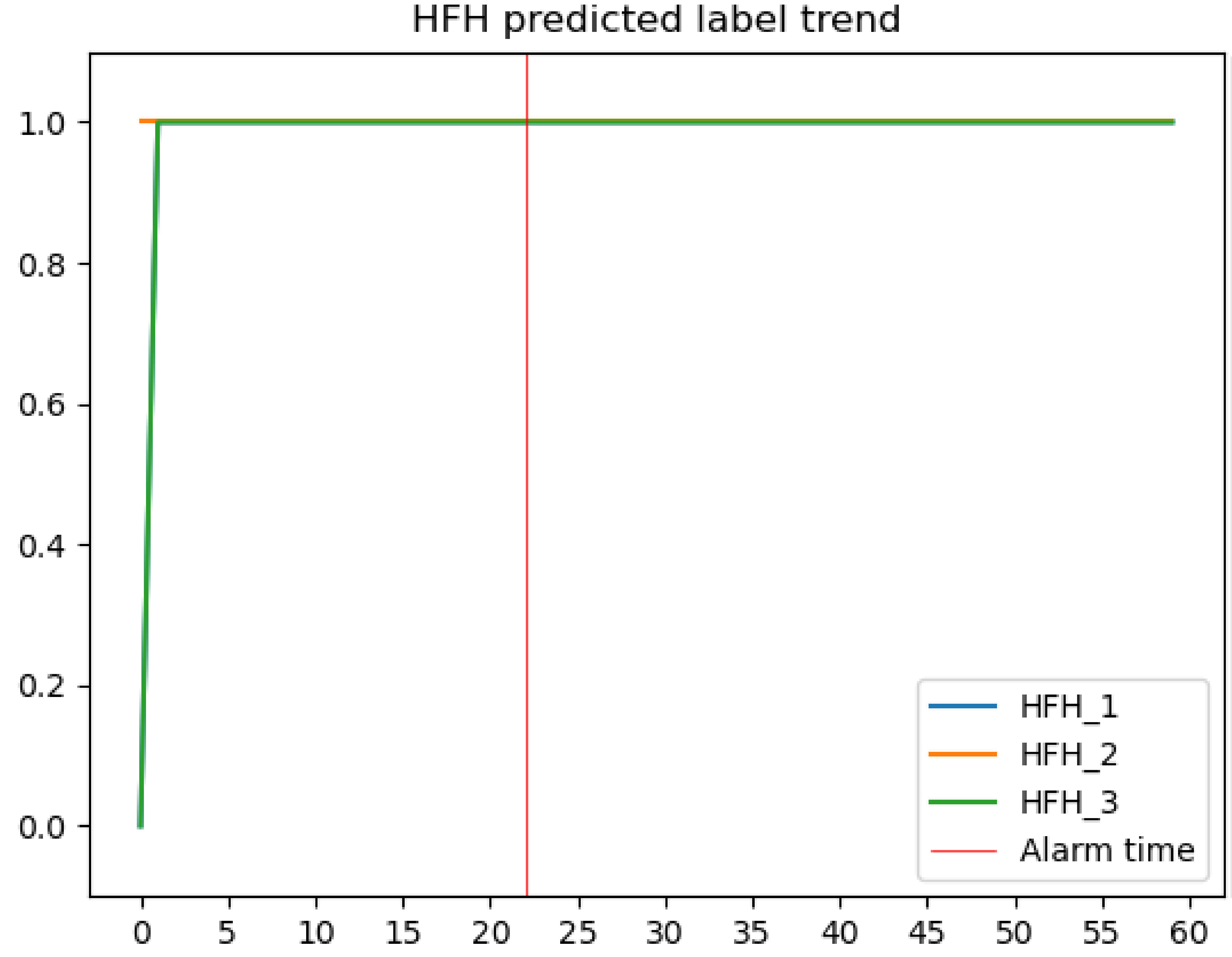
- ❖ The test is done in each second
- ❖ The test results are divided into normal and abnormal state
- ❖ An abnormal state is recognized as the presence an alarm
- ❖ An abnormal state detection model is evaluated with detection time and alarm time

	Params 1	….	Params 689				
1 sec				→	Test	→	Normal
2 secs				→	Test	→	Normal
….				….		….	
60 secs				→	Test	→	Normal

Case study

Test results

- ❖ All normal states were classified as normal states
- ❖ Abnormal state detections were possible faster than the alarm
- ❖ An abnormal detection shows consistent results after detection time



State	Accuracy
Normal	1.0

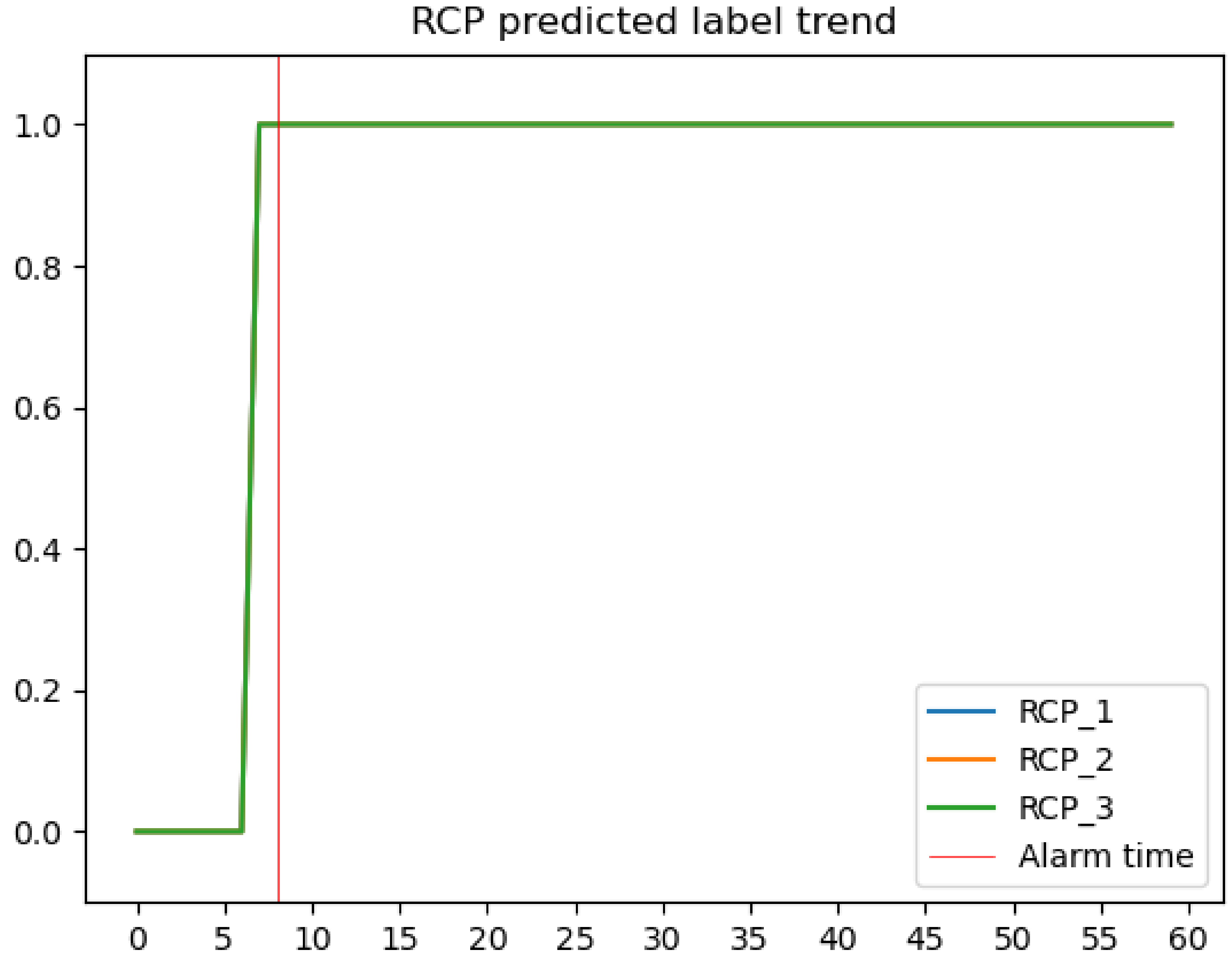
States	Alarm time	Detection time
SGTL	22	6
CHRG	0	0
LTDN	6	0
CDS	-	3
POSRV	1	0
CWS	34	2
MSIV	42	2
RCP	8	7
MSS	38	2
PZR	51	7
CCW	23	1
LFH	17	3
HFH	22	1
MFW	35	2
TCS	18	0

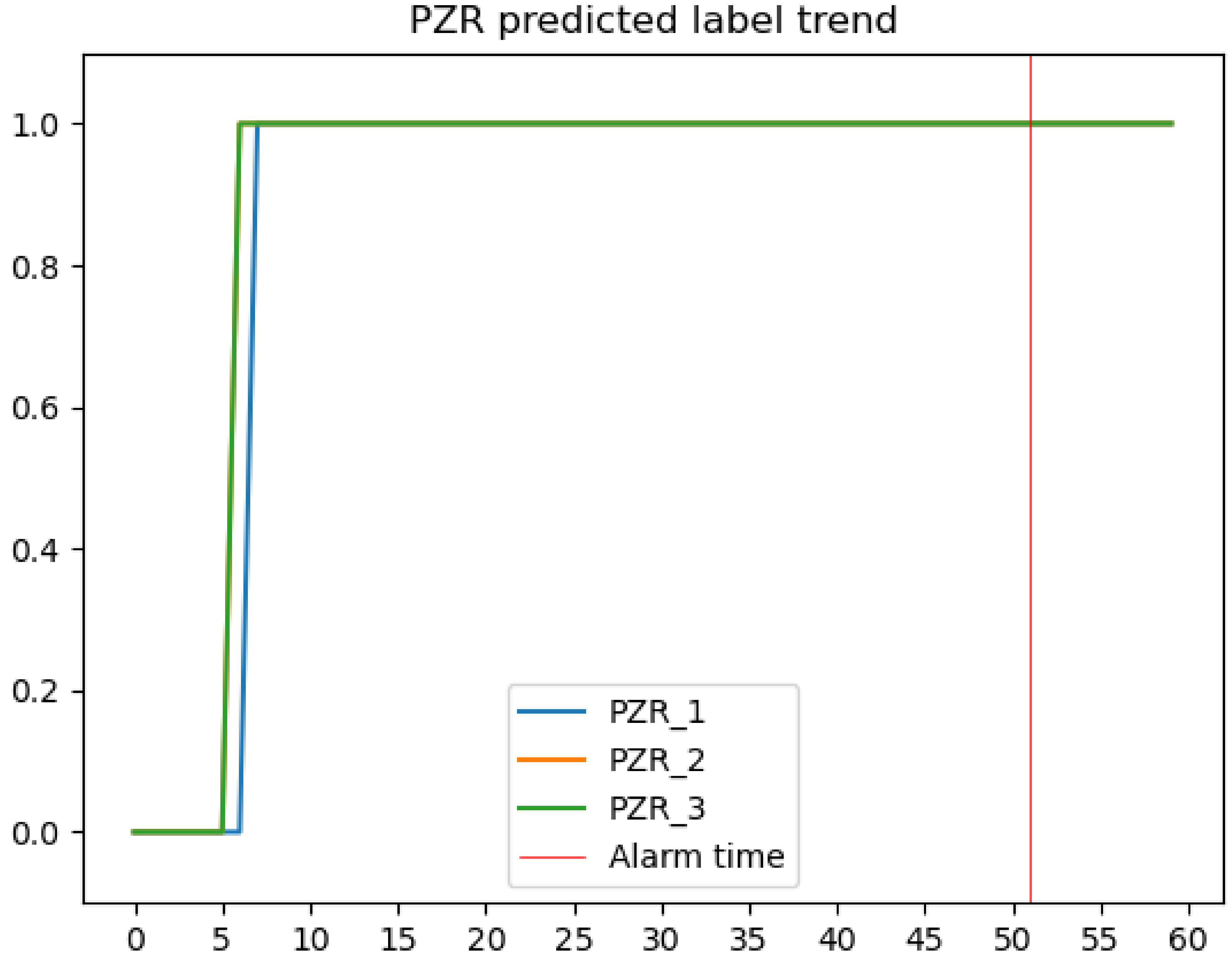
Case study

Test results

- ❖ Even in two cases with late detection time, detection time is faster than the alarm time
- ❖ For PZR abnormal states, detection time was much faster than the alarm time

States	Alarm time	Detection time
RCP	8	7
PZR	51	7





Conclusion

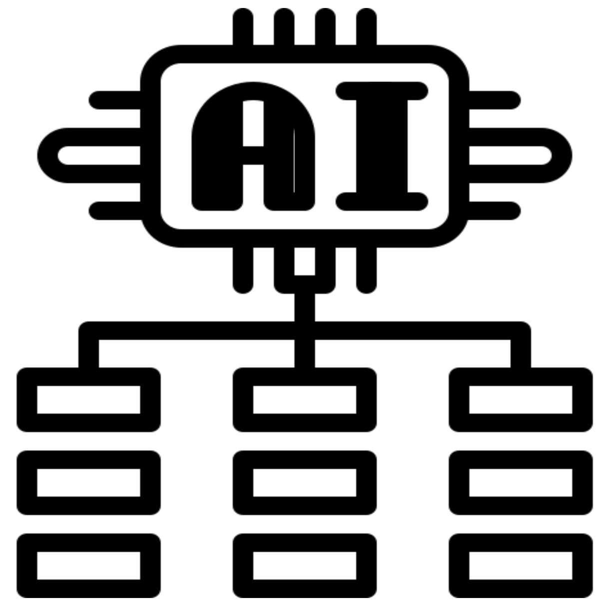
- Since an abnormal detection model based on Deep SVDD trains only normal state data, data production is relatively free and applicable to various abnormal states
- The accuracy of normal state is 100% even with noise and offset
- The proposed model shows faster detection time than alarm time
- **Faster abnormal detection than alarm time can secure execution time of operators**
- **As a result, this study can expand execution time to take actions of operators under an abnormal state and contribute to reducing human error**

Further study

❖ Using the proposed model, the abnormal state diagnosis models **don't need to learn normal state data**

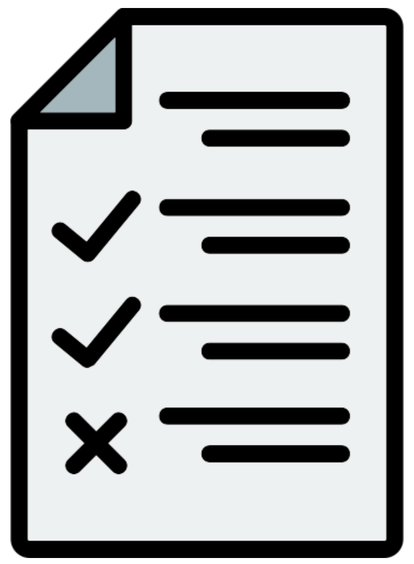
❖ As a result, we will show **higher accuracy of the abnormal states diagnosis model due to decreased number of labels through the introduced framework**

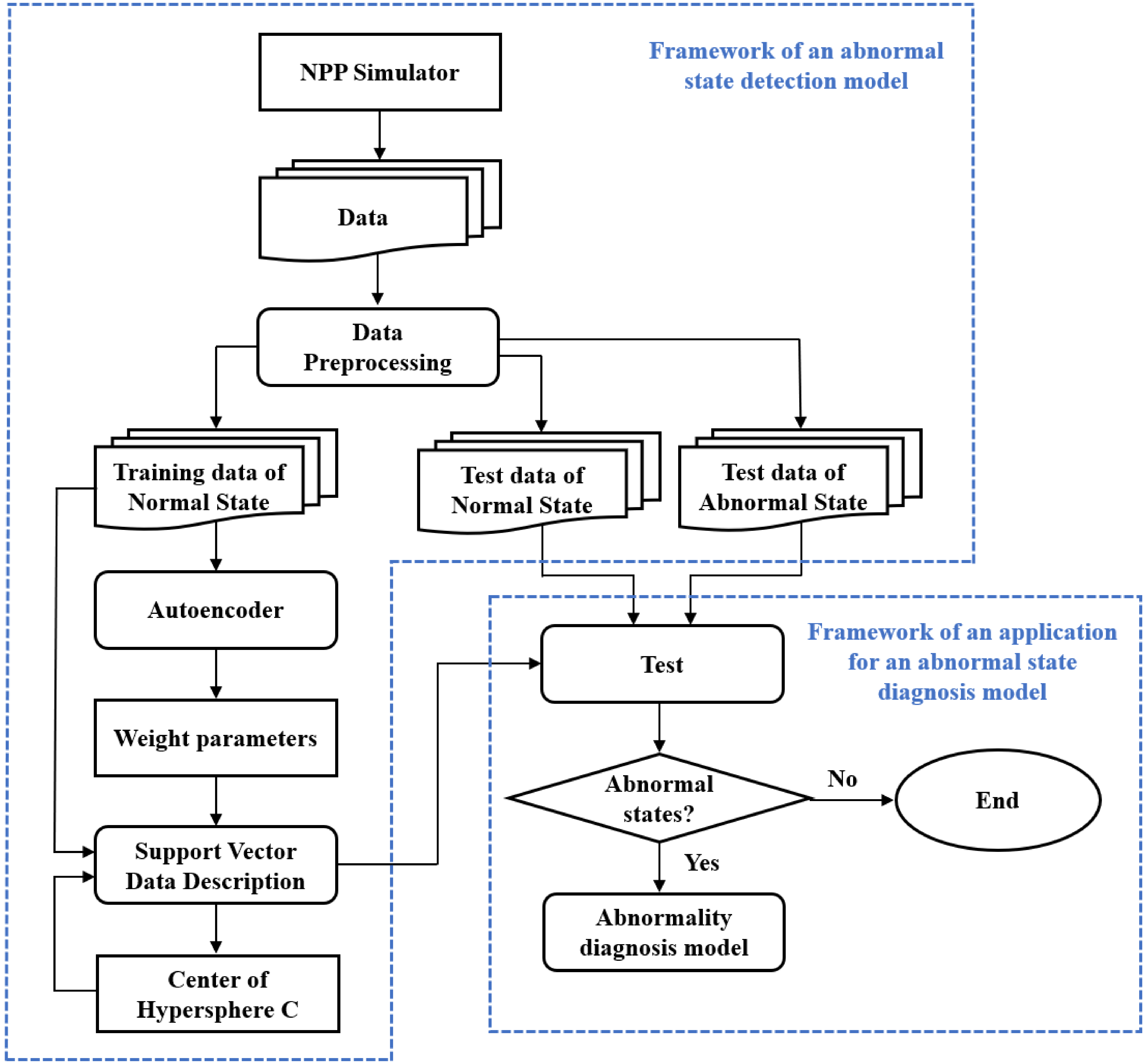
Less labels of a classifier model



Diagnosis

Higher accuracy of a classifier model





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