Machine learning application for RUL prediction of experimental bearings and liquid hydrogen releases

RAMS Seminar

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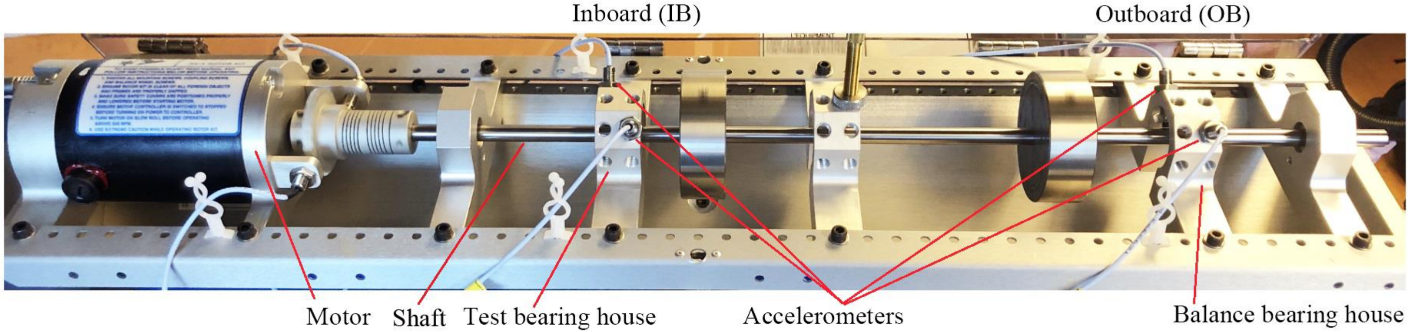
Outline – RUL prediction of experimental bearings

- Data Description
- Objectives
- Methodology
- Results and Discussion

Data Description



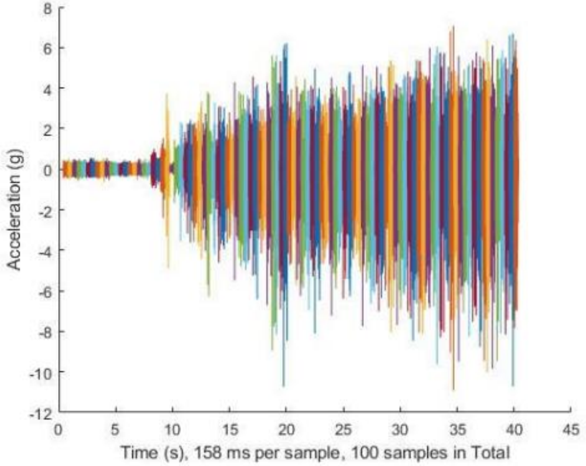


TABLE II
BEARINGS AND THEIR NUMBER OF SAMPLES.

Bearing	B1	B2	B3	B4	B5
Number of samples	110	35	146	106	77
Bearing	B6	B7	B8	B9	B10
Number of samples	248	150	143	114	115

Objectives

- Select the best health indicator(s) to predict the RUL of bearings
- Predict the RUL of bearings accurately

Methodology

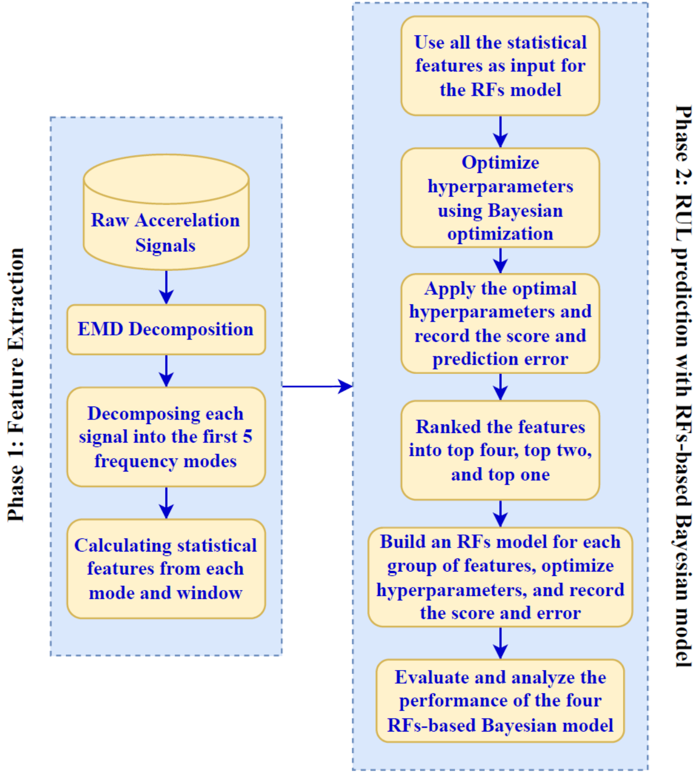


Fig. 1. The framework of the proposed method.

Methodology - Features

Table 1, Statistical features

Feature	Kurtosis	RMS	Crest factor	Skewness
Formula	$K = \frac{\sum_{i=1}^{M}(x_i - m)^4}{(M-1)\sigma^4}$	$RMS = \sqrt{\frac{1}{M}\sum_{i=1}^{M} x_i^2}$	$CF = \frac{\max(\lvert x_i \rvert)}{\sqrt{\frac{1}{M}\sum_{i=1}^{M} x_i^2}}$	$S = \frac{\sum_{i=1}^{M}(x_i - m)^3}{(M-1)\sigma^3}$
Feature	Mean	Shape factor	Impulse factor	
Formula	$Mean = \frac{1}{M}\sum_{i=1}^{M} x_i$	$SF = \frac{\sqrt{\frac{1}{M}\sum_{i=1}^{M} x_i^2}}{\frac{1}{M}\sum_{i=1}^{M}\lvert x_i \rvert}$	$IF = \frac{max\lvert x_i \rvert}{\frac{1}{M}\sum_{i=1}^{M}\lvert x_i \rvert}$	

Evaluation Metrics

- Score function

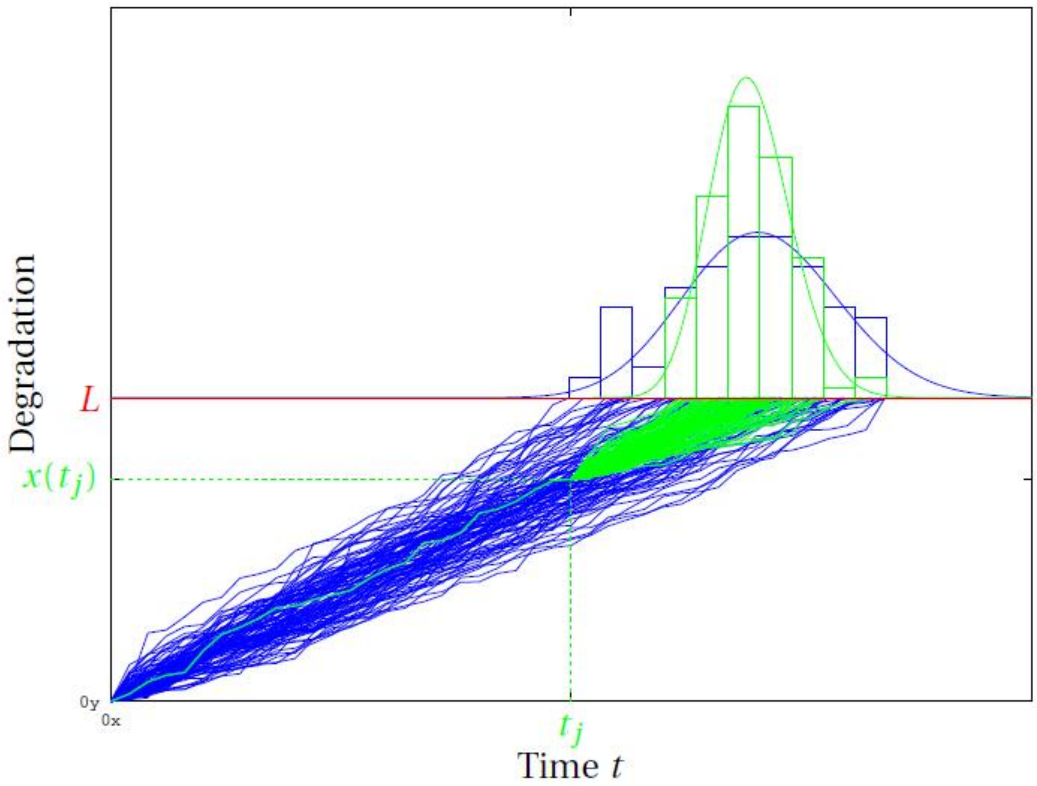
$$A_i = \begin{cases} exp^{(-\ln 0.5).\left(\frac{Error}{5}\right)} & if\ Error \leq 0 \\ exp^{(+\ln 0.5).\left(\frac{Error}{20}\right)} & if\ Error > 0 \end{cases}$$

$$Score = \frac{\sum_{i=1}^{n} w_i \times A_i}{\sum_{i=1}^{n} w_i}$$

- RMSRE

$$RMSRE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{Act\ RUL - \widehat{RUL}}{Act\ RUL}\right)^2}$$

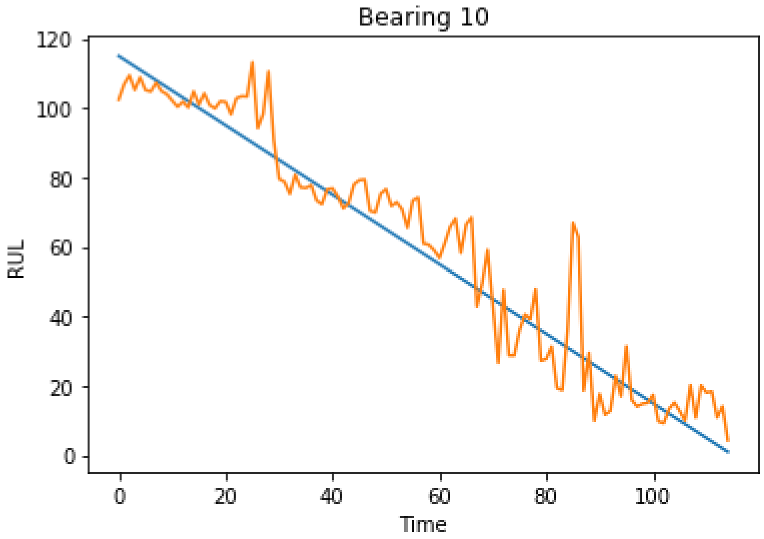
Stochastic Approach – Wiener Process



ML Approach

- There are 10 bearings dataset from the experiment
- Predict the RUL of 1 bearing by using the other 9 bearings dataset
- Use all of the available features as input to the RF model and RUL as the output
- Rank the features based on the importance
- Record the score and RMSRE

Result Example



feature	importance
SFH	0.367665
rH	0.346226
kH	0.226374
IFH	0.029584
avgH	0.010531
crestH	0.010112
sH	0.009509

```
Score_B10
```

[0.940774694269068]

```
RMSRE_B10
```

[0.8846260520798368]

Approach – cont’d

- Select only the top 4 features as input and record the score and RMSRE
- Select only the top 2 features as input and record the score and RMSRE
- Select only one features as input and record the score and RMSRE

Result Example

```
Score_B10
[0.940774694269068, 0.94115665621009, 0.9185767013343269, 0.8243940969819221]
```

```
RMSRE_B10
[0.8846260520798368, 0.8770273135913559, 1.2782504227561595, 3.0627102555628 19]
```

Results Summary

TABLE IV
THE SCORE OF RUL PREDICTIONS FOR EVERY BEARING.

Score	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	Average
All features	0.7621	0.7950	0.9277	0.9533	0.8760	0.9648	0.8809	0.9516	0.9094	0.9461	0.8967
4 features	0.7636	0.7853	0.9307	0.9580	0.8643	0.9634	0.8972	0.9537	0.9164	0.9487	0.8981
2 features	0.7761	0.8597	0.9362	0.9612	0.9329	0.9641	0.8447	0.9603	0.9135	0.9429	0.9092
1 feature	0.9536	0.6414	0.8151	0.8413	0.8096	0.9645	0.8532	0.8266	0.7917	0.8306	0.8328

TABLE V
THE RMSRE OF RUL PREDICTIONS FOR EVERY BEARING.

RMSRE	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	Average
All features	2.6739	2.2487	1.3654	0.7220	1.1861	0.8493	1.4983	0.8499	1.4479	0.9599	1.3801
4 features	2.6187	2.2637	1.0971	0.6671	1.4759	0.9307	1.3785	0.8547	1.4315	0.8149	1.3533
2 features	2.3878	1.3728	1.2691	0.6417	0.7147	0.8891	1.8001	0.7249	1.2908	1.1332	1.2224
1 feature	0.5278	4.2387	4.3198	3.4316	1.7146	0.8916	1.8849	5.5522	7.3177	2.9226	3.2802

Best Results

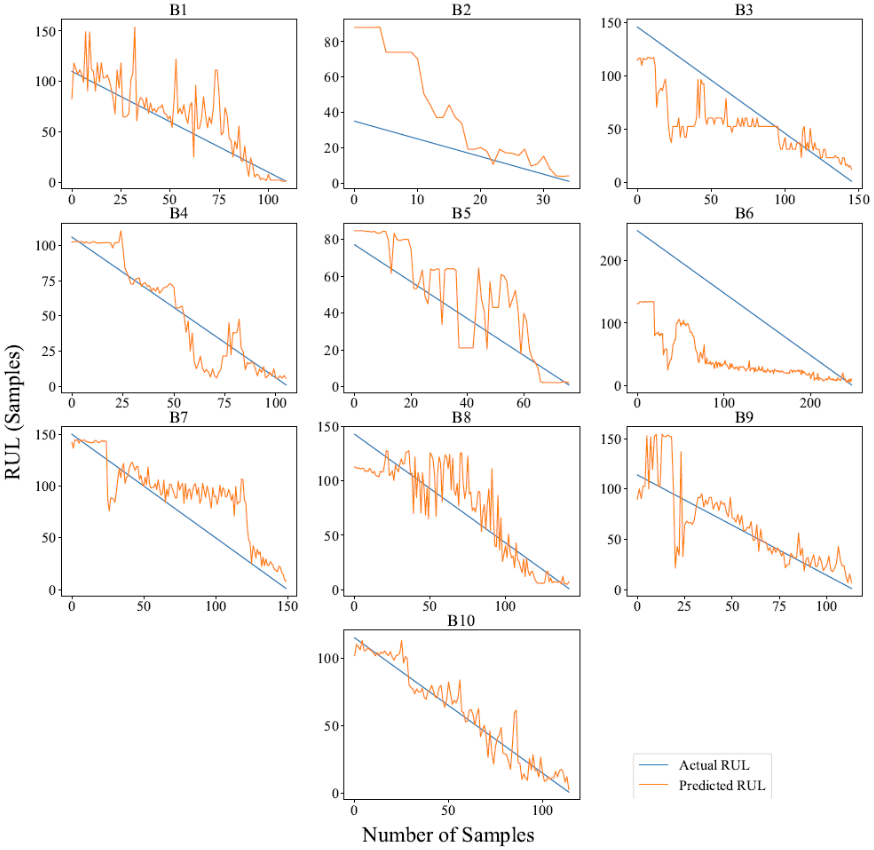


Fig. 5. The best RUL prediction of every bearing.

Comparison

TABLE VI
SCORE AND RMSRE OF ALL METHODS.

Method	Avg. Score	Avg. RMSRE
Proposed method	**0.9092**	**1.2224**
Conventional RFs	0.8856	1.3375
ANN	0.7735	6.5496
SVR	0.7581	7.5216
LASSO	0.8196	3.6325
Wiener process	0.8606	2.6301

Contributions

- A framework to construct health indicators is proposed to determine the best feature for RUL prediction.

- A novel data-driven approach is proposed by utilizing the proposed health indicator framework, random forest, and Bayesian optimization.

- The proposed RUL prediction approach is verified by real-world datasets and compared with other data-driven and model-based approaches for RUL prediction of bearings.

Outline- Prediction of liquid hydrogen releases

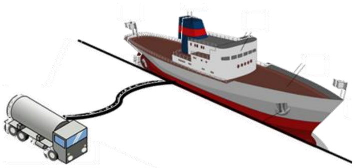
- Experimental studies
- Liquid hydrogen release hazards
- Objectives
- Database description
- Results

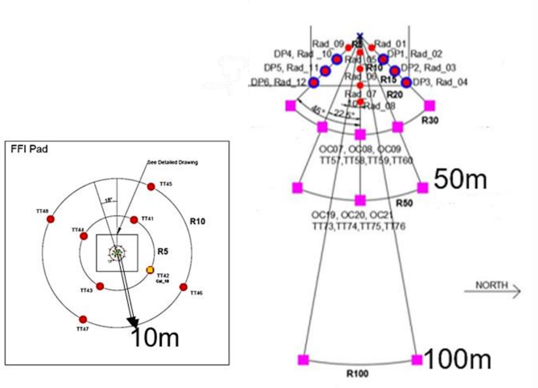
Experimental studies

The FFI has performed a series of experimental tests simulating accidental spill of LH_2 for maritime applications.

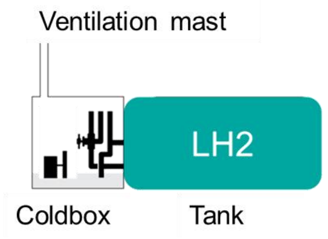
Two different kinds of tests have been performed:

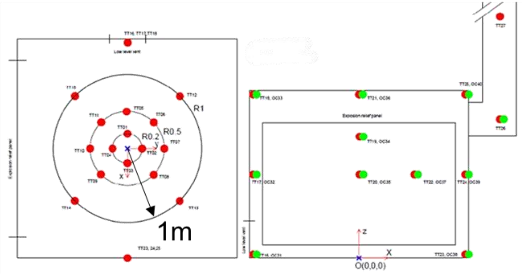
- outdoor leakage studies → to simulate spill of LH_2 from a bunkering operation





- closed room and ventilation mast studies → to simulate spill of LH_2 in the technical room connected to the storage tank





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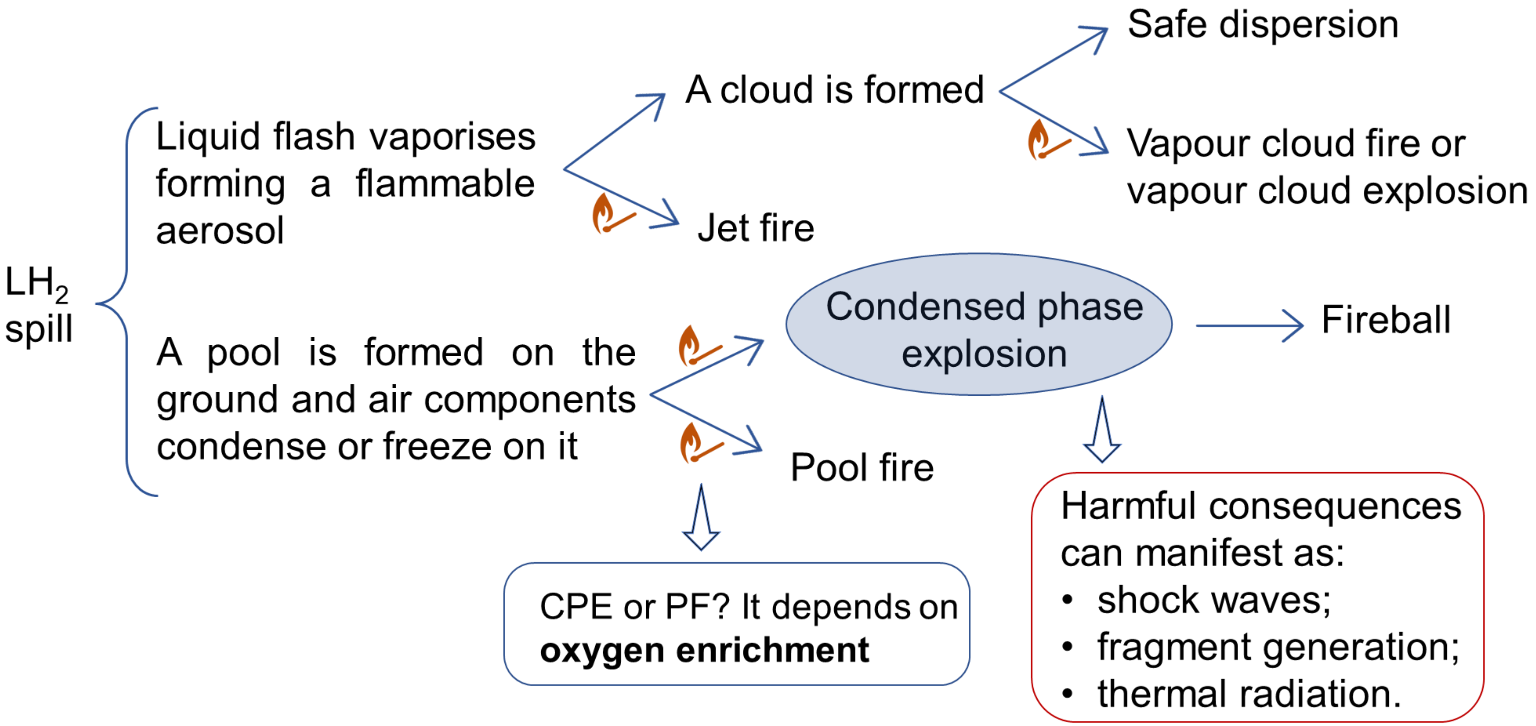
Liquid hydrogen release hazards



Objectives

- Predict the occurrence of oxygen condensation and solidification during an LH_2 accidental spill

- Predict whether the H_2 concentration > LFL due to the LH_2 evaporation

Database description

Three different databases have been developed:

First Database

- Outdoor leakage studies
- Condensation or freezing of air components prediction

Second Database

- Outdoor leakage studies
- Hydroge concentration within the gas cloud prediction

Third Database

- Closed room studies
- Condensation or freezing of air components prediction

General structure of the databases:

Feature 1	*Feature 2*	...	*Feature n*	*Label*
t_0			TT_0 (or HC_0)	1
...			...	...
t_n			TT_f (or HC_f)	0

Database description

Common features

- ambient P, T and humidity
- tank internal T and P
- Instruments (TT and HC) measurements and locations
- release rate and orientation

First Database	Second Database	Third Database
Additional features: • wind conditions **Label:** • liquid oxygen formation • solid oxygen formation	**Additional features:** • wind conditions **Label:** • hydrogen concentration above the LFL	**Additional features:** • sealing • purge **Label:** • liquid oxygen formation • solid oxygen formation

Label →

$$label = 1\ if\ T < T_b\ (or\ T_m)\ within\ 200\ s$$
$$label = 1\ if\ C_{H_2} > LFL\ within\ 200\ s$$

sprinklers' average response time

Results

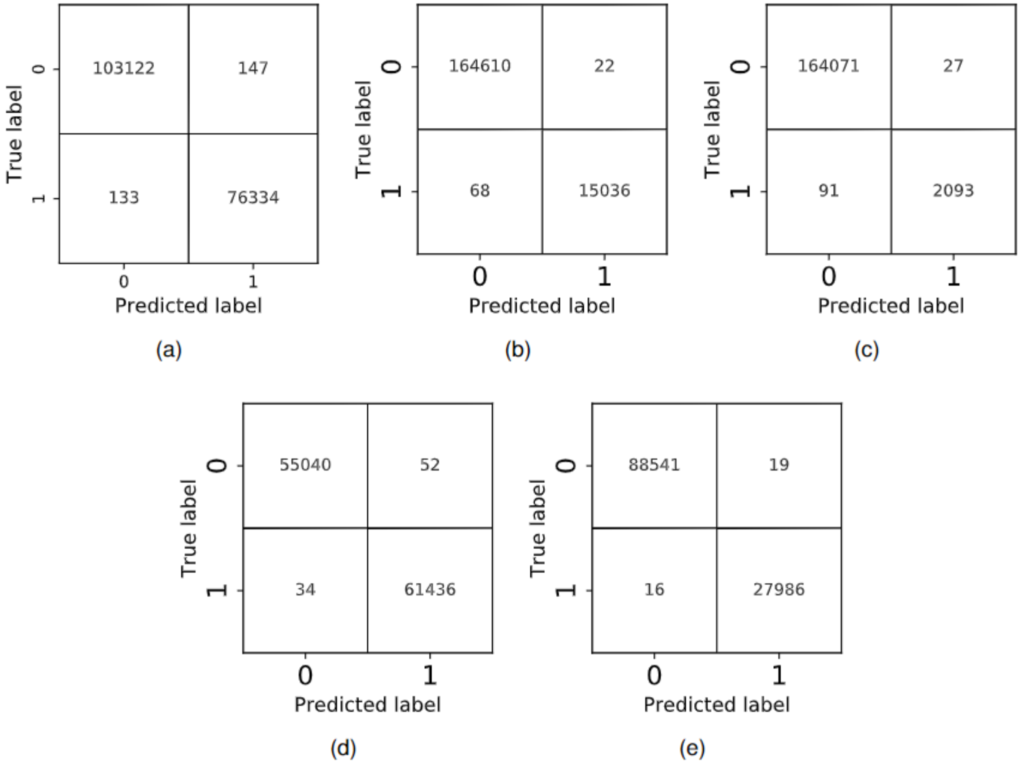


Fig. 2. Confusion matrices for the labels (a) first database - liquid oxygen, (b) first database - solid oxygen, (c) second database - H_2 concentration >LFL, (d) third database - liquid oxygen, and (e) third database - solid oxygen.

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Results

TABLE II
PERFORMANCE METRICS OF RFS MODEL FOR ALL DATABASES.

Label	Accuracy	Precision	Recall	F1	AUC-PR
First database (liquid oxygen)	0.9984	0.9981	0.9983	0.9984	0.9985
First database (solid oxygen)	0.9995	0.9985	0.9955	0.9984	0.9972
Second database (H_2 concentration >LFL)	0.9993	0.9873	0.9583	0.9861	0.9731
Third database (liquid oxygen)	0.9993	0.9992	0.9994	0.9993	0.9994
Third database (solid oxygen)	0.9997	0.9993	0.9994	0.9996	0.9994

TABLE III
PERFORMANCE COMPARISON OF RFS MODEL AND LINEAR MODEL (LM) IN [5] FOR ALL LABELS.

Label	Accuracy		Precision		Recall		AUC-PR	
	LM	RFs	LM	RFs	LM	RFs	LM	RFs
Liquid oxygen	0.9020	**0.9984**	0.8480	**0.9981**	0.9360	**0.9983**	0.9490	**0.9985**
Solid oxygen	0.9570	**0.9995**	0.830	**0.9985**	0.6130	**0.9955**	0.8070	**0.9972**
H2 concentration >LFL	0.9880	**0.9993**	0.6490	**0.9873**	0.1840	**0.9583**	0.3660	**0.9731**

Contributions

- A machine learning model was developed to predict the possibility of oxygen phase change depending on the operative condition.

- The model demonstrated accurate and reliable predicting capabilities.

- The outcomes of the model can be exploited to select effective safety barriers such as a water deluge system to prevent the oxygen change phase.