Acoustic Insights into Flow Condensation Mechanisms

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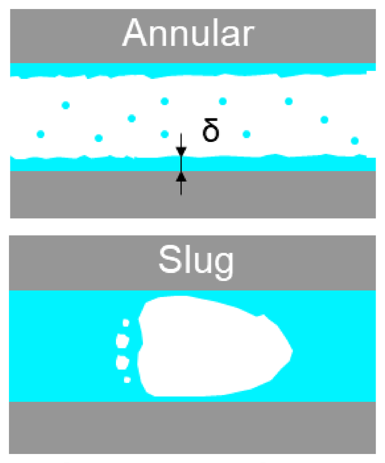
Motivation



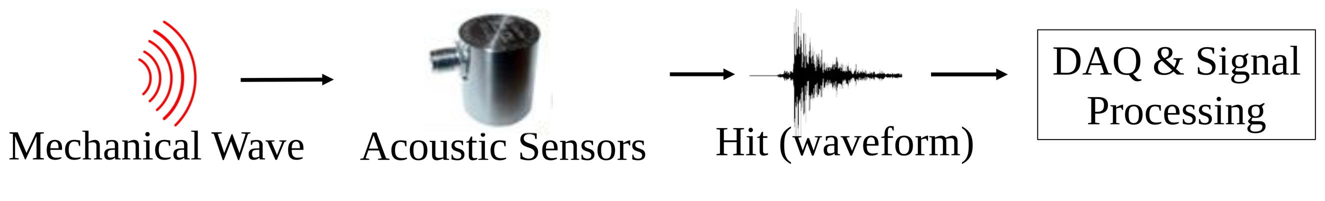
Flow regimes during flow condensation

- Flow condensation occurs in a variety of thermal-fluid applications, with distinct heat transfer characteristics observed across different flow regimes.
- Interfacial instabilities in flow condensation have potential to degrade thermal performance.
- Traditional analysis of flow condensation, such as thermofluidic measurements or high-speed visualization, are not always available and lack the sampling rate required to capture rapid dynamics.

Innovative Solution

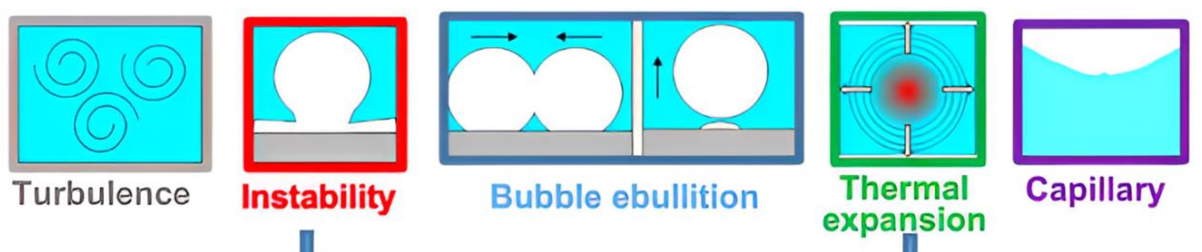
Acoustic Sensing Techniques

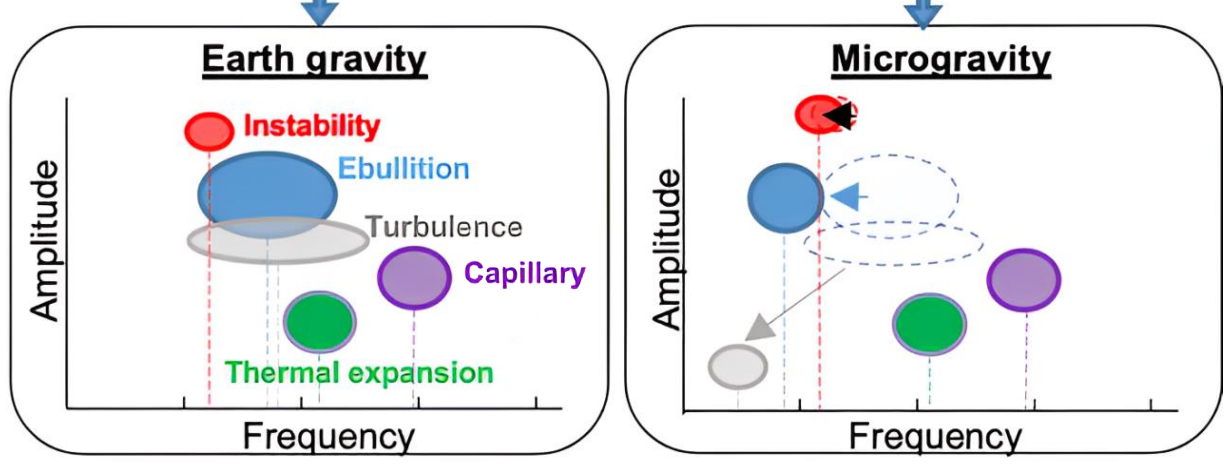
- Does not require direct visualization access, providing greater flexibility in flow condensation studies
- Offers a better time resolution compared to optical imaging, enabling the capture of high-frequency characteristics
- Enables non-destructive measurement of acoustic waves, minimizing impact on the flow condensation dynamics



Diagrammatic representation of the acoustic monitoring process

Acoustic Signatures of Transport Processes





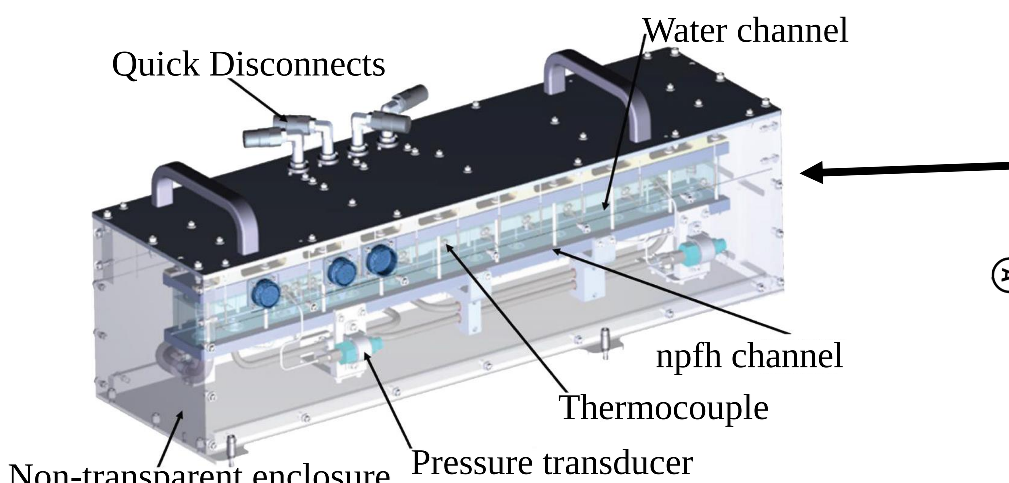
- Acoustic signatures may fully decouple under microgravity

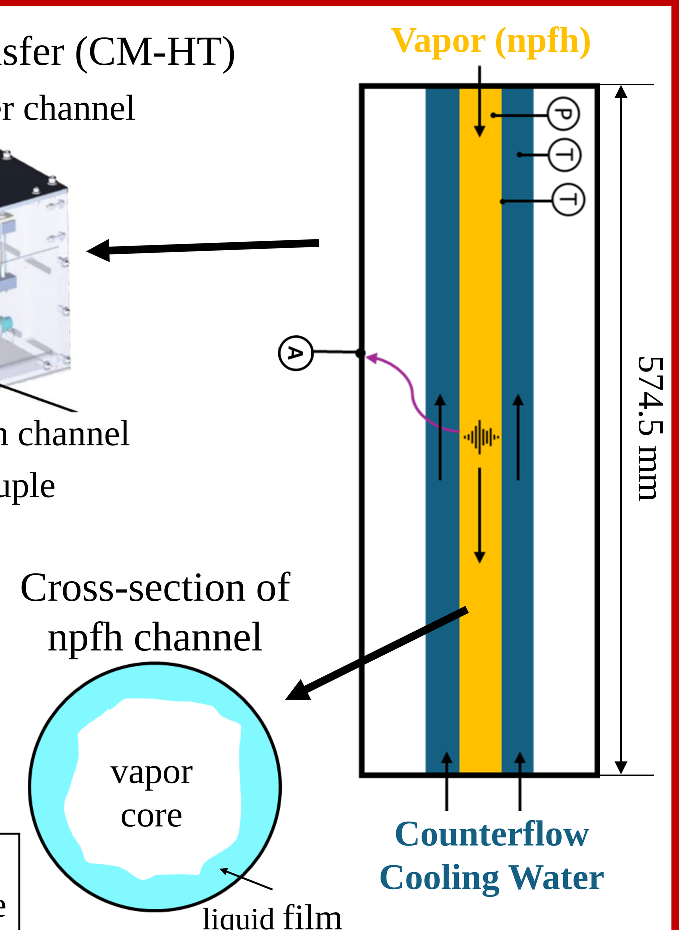
Objective

Using non-destructive acoustic sensors to characterize flow condensation and identify dominant transport mechanisms during flow regime transitions under gravity and microgravity

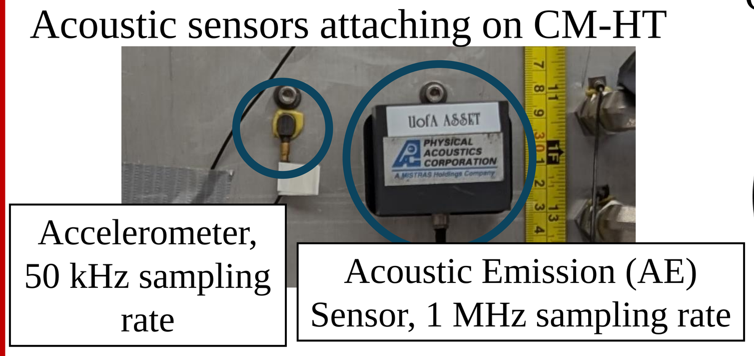
Experimental Setup

NASA Condensation Module – Heat Transfer (CM-HT)





Acoustic sensors attaching on CM-HT



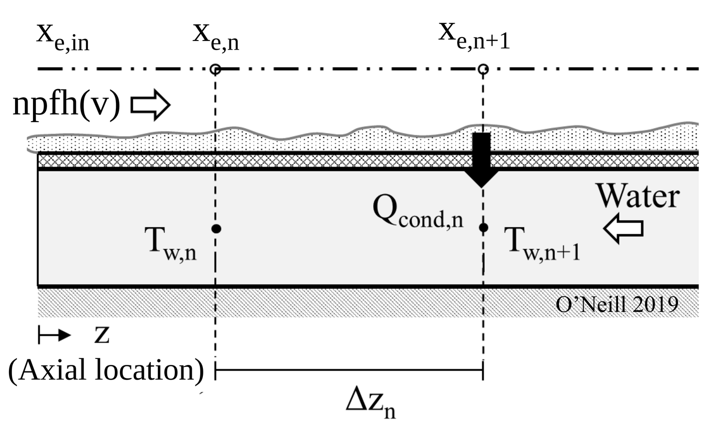
System Overview

- Test fluid: normal perfluorohexane (npfh)
- nPFH flow rate: 2 g/s – 25 g/s
- Water flow rate : up to 27 g/s
- Vapor inlet conditions: subcooled, saturated, or superheated

Testing Conditions

Flow Orientation	Vertical downflow
Target Inlet Quality	1.15/ 1.0 /0.8 /0.6
Gnpfh kg/m² s	115-419
Gwater kg/m² s	324

Vapor Quality Calculation



Schematics of vapor quality calculation

Inlet quality of saturated vapor:

$$x_{e,in} = \frac{Pwr_{HT} - \dot{m}_v C_{p,l,v}(T_{v,sat} - T_{HT,in})}{\dot{m}_v h_{fg,v}}$$

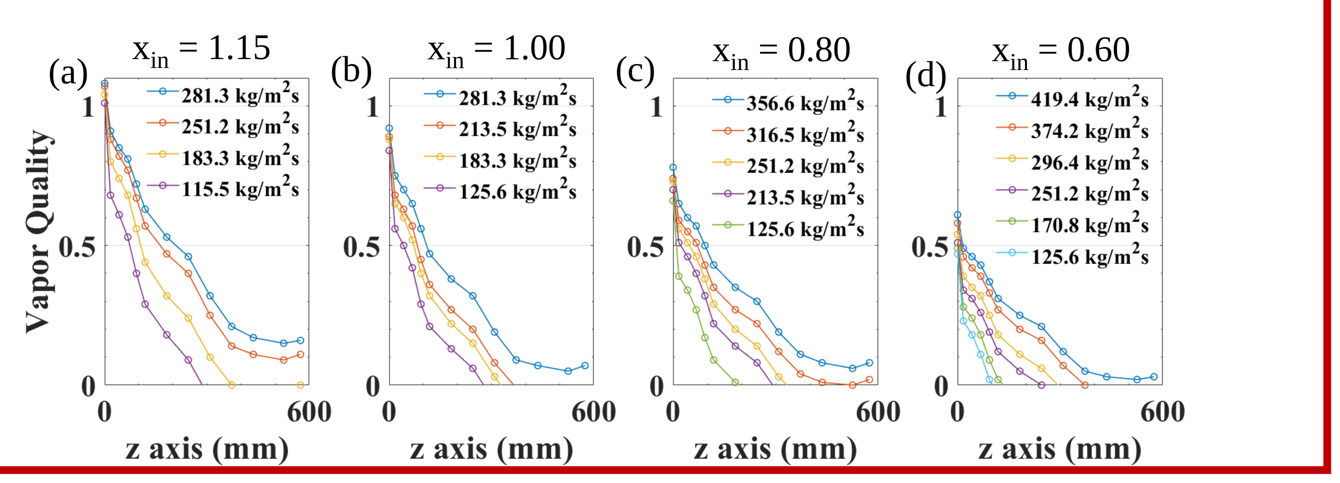
Inlet quality of superheated vapor:

$$x_{e,in} = 1 + \frac{C_{p,g,v}(T_{v,in} - T_{v,sat})}{h_{fg,v}}$$

Subsequent local quality :

$$x_{e,n+1} = x_{e,n} - \frac{\dot{m}_w C_{p,w} \Delta T_w}{\dot{m}_v h_{fg,v}}$$

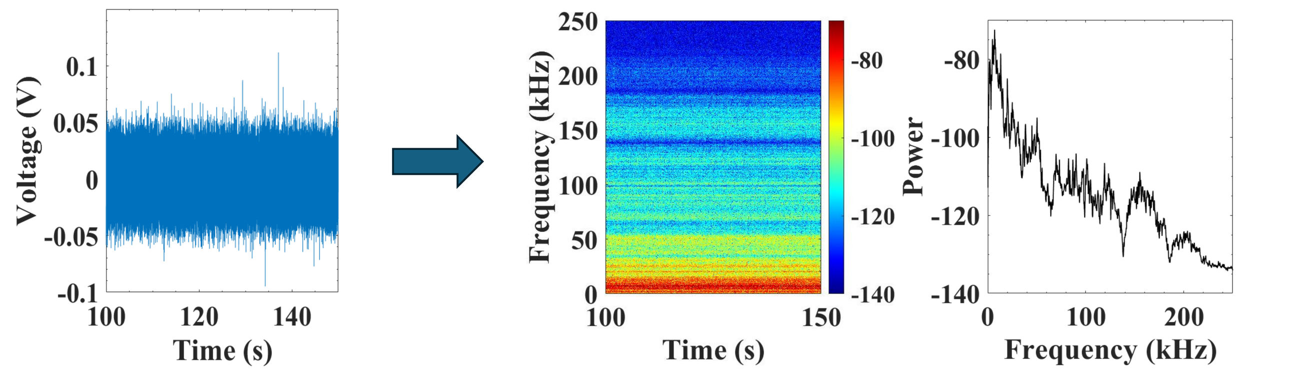
Vapor quality profiles at various Gnpfh and set inlet vapor qualities



Acoustic Signal Processing

Short Time Fourier Transform (STFT)

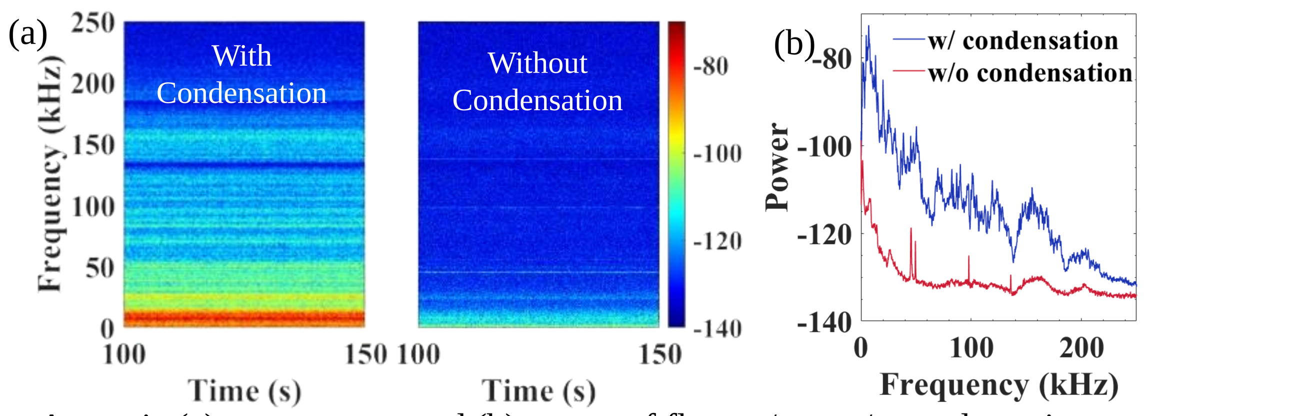
- Convert raw sensor data to frequency domain using STFT



Acoustic Raw Data — Acoustic Spectrogram — Acoustic Power Spectrum

Results

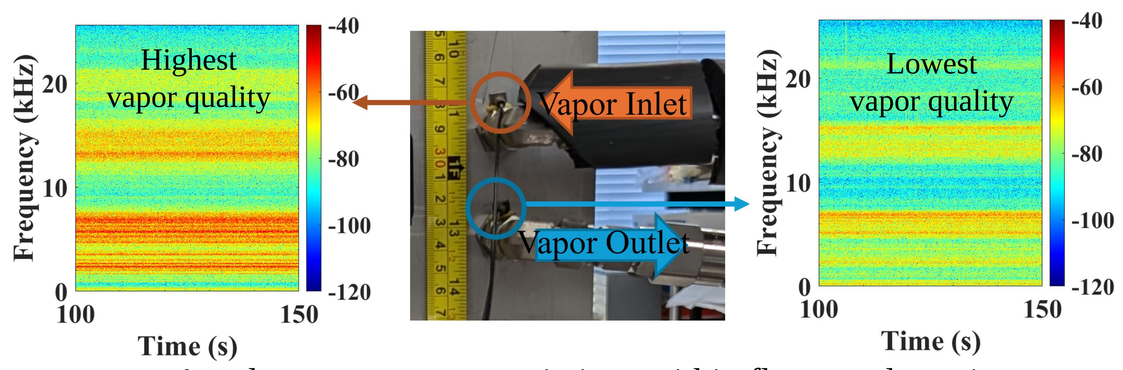
Acoustic Signatures Comparison between flows w/ and w/o condensation



Acoustic (a) spectrogram and (b) power of flow w/ vs. w/o condensation

- Flow condensation generates significant acoustic power
- Broad frequency interaction (250 kHz) during condensation
- Minimum acoustic power in non-condensation flow

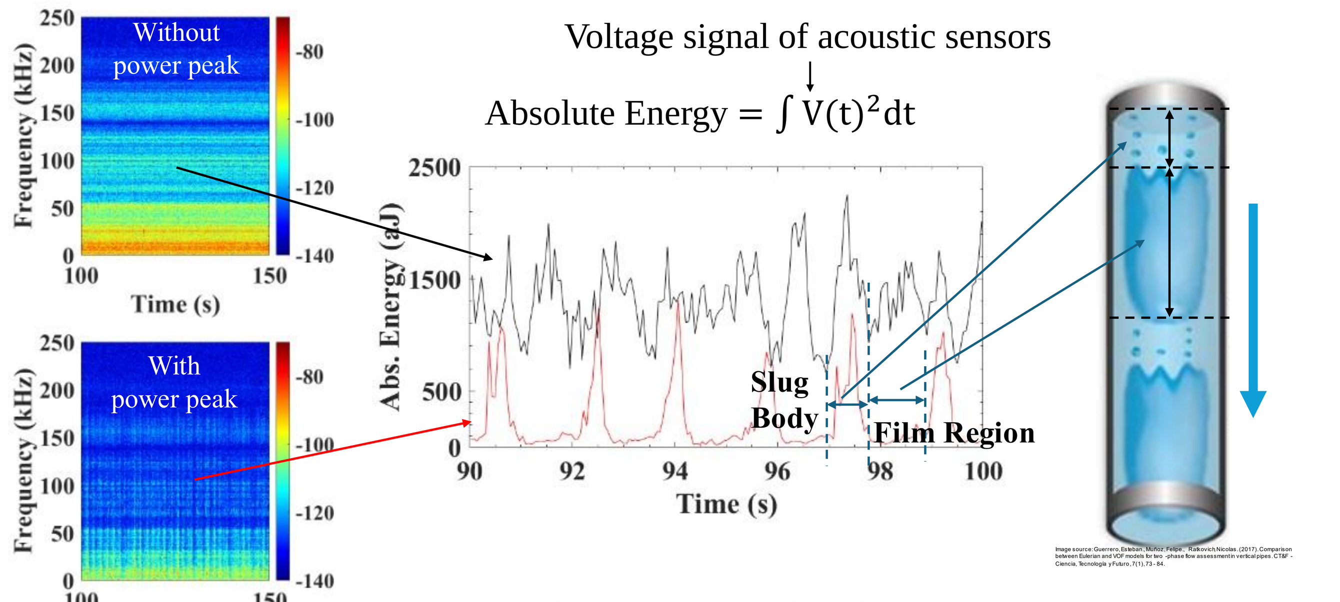
Effect of Vapor Quality on Accelerometer Power



Accelerometer power variations within flow condensation

- Stronger accelerometer power associated with higher vapor quality

Flow Condensation Regime Identification

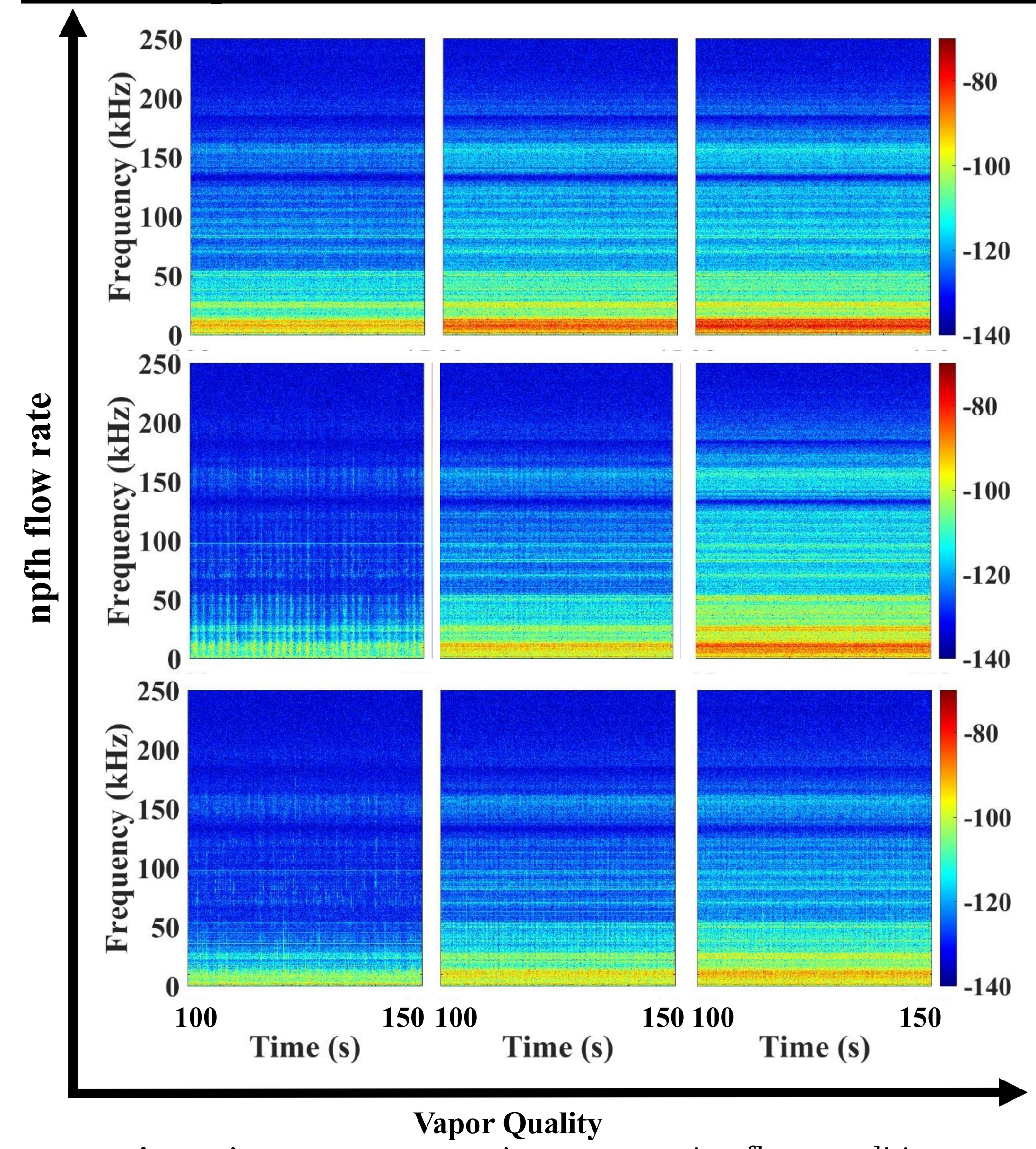


Acoustic identification of slug flow regime

- Periodic vertical power bands observed at certain acoustic spectrograms
- Periodic peaks in absolute energy aligned with slug flow regime characteristics

Results (cont.)

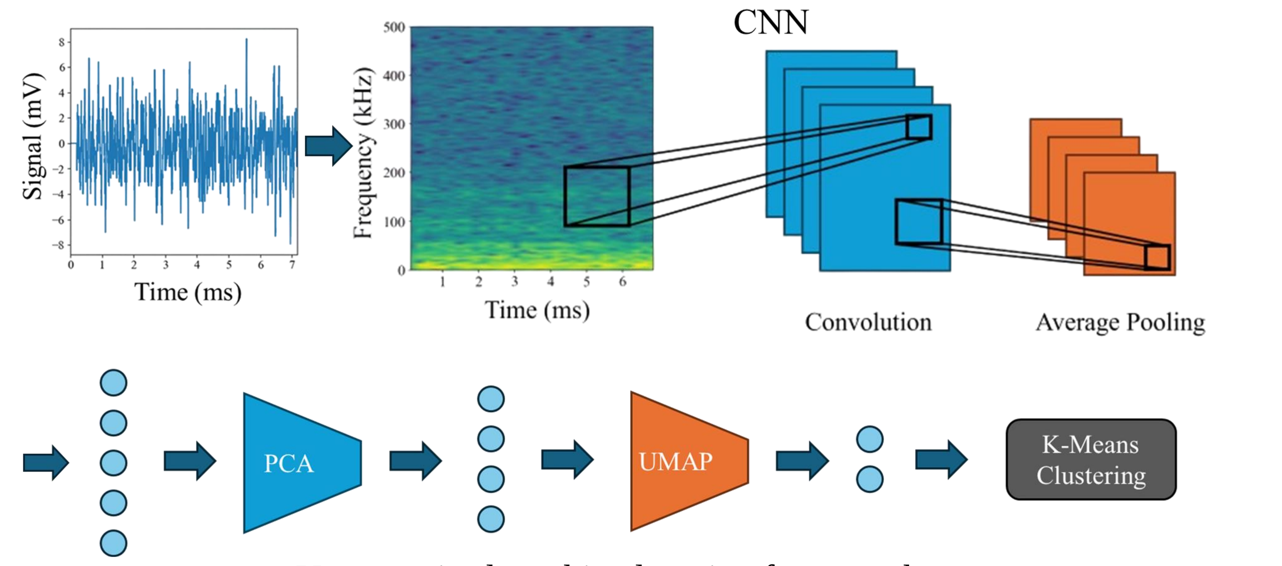
Relationship between Acoustic Power and Flow Condensation



Acoustic spectrogram matrix across varying flow conditions.

- Acoustic power intensifies with increasing vapor flow rate and quality

Acoustic Signatures Classification via Unsupervised Machine Learning (UML)



Unsupervised machine learning framework

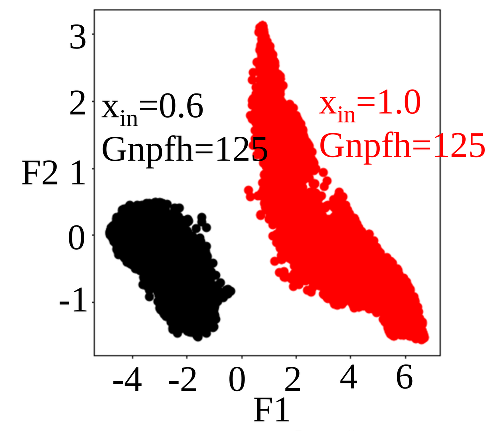
Purpose for each step

CNN (Convolutional Neural Network):
- Extracts features using convolutional layers and filters

PCA (Principal Component Analysis):
- Linearly reduces CNN features, focusing on PCs to denoise data

UMAP (Uniform Manifold Approximation and Projection):
- Nonlinearly reduces data, preserving local and global structures

K-Means Clustering
- Organizes data into clusters, evaluated by the Adjusted Rand Index (ARI)



Representative result of classification of flow condensation

Performance of unsupervised machine learning

Test Set	Set Inlet Vapor Quality	Gnpfh	Accuracy
1	0.6, 1	125	0.9035
2	0.6, 1, 1.15	178	0.9480
3	0.8, 1	213	0.9996
4	0.6, 0.8, 1.15	250	0.9723
5	0.6, 1, 1.15	285	1.0000
6	0.6, 0.8	305	0.9980
7	0.6, 0.8	364	0.9894

- UML effectively classifies acoustic signatures by vapor qualities.

Summary

- Flow condensation exhibited significantly stronger acoustic signals than single phase liquid flow.
- Acoustic signatures proved effective in capturing flow condensation dynamics.
- Slug flow regime was effectively identified through distinct acoustic patterns.
- Unsupervised machine learning with feature extraction enhance raw data retention and facilitate the classification of flow condensation.
- Future testing will be conducted under microgravity.

Acknowledgment

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