POWER & MOBILITY

# Detecting Damage Using Acoustic Emission During Evaluation of High-Pressure Fuel Pump Durability with Low-Viscosity Fuels


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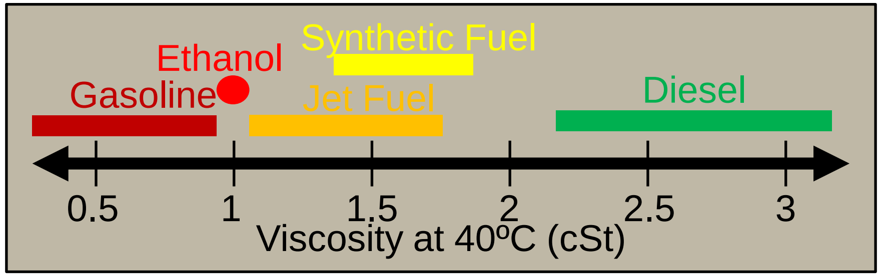
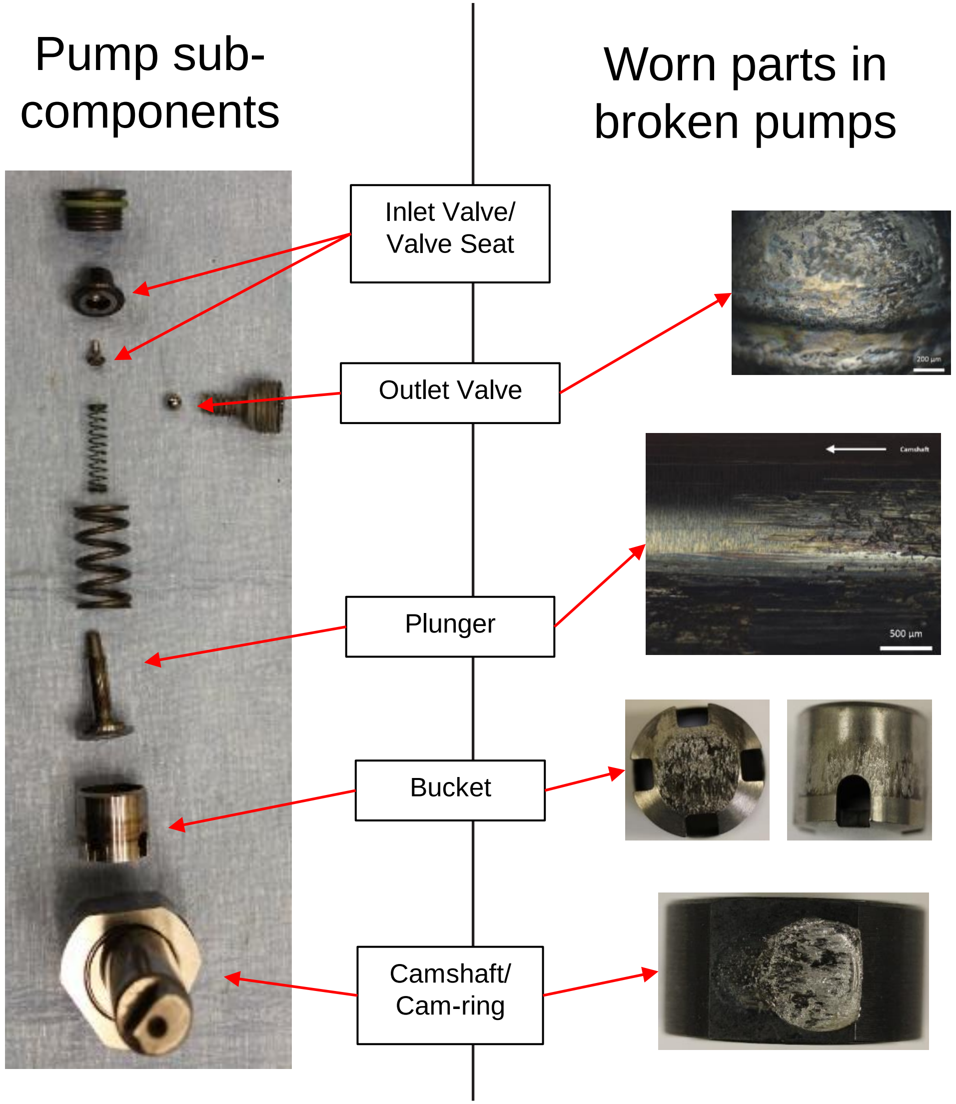
# PROBLEM

1. Diesel engines require high-pressure fuel pumps (HPFPs)
2. The fuel pumps rely on fuel for lubrication
3. Damage is difficult to detect/diagnose failure during operation
4. <u>Fuel pump life is dependent on fuel properties (viscosity, lubricity)</u>

How do low lubricity (<1 cSt) fuels affect pump performance?



# OBJECTIVE

## Objectives

1. Characterize fuel pump performance during low lubricity fuel pump operation

2. Explore the potential of acoustic emission sensors for non-destructive early fault detection

High-Pressure Fuel Pump

## Approach

– Low-Viscosity Fuel Durability Experiments
  - Operate with low-viscosity fuel until failure
  - Analyze damaged components to determine root-cause of failure

– Sensor Analysis and Non-destructive Pump Diagnostics
  - Acquire acoustic emission sensor data from fuel pump durability experiments
  - Process sensor data for interpretation
  - Classify component state from processed data
  - Automate the previous three steps using machine learning algorithms

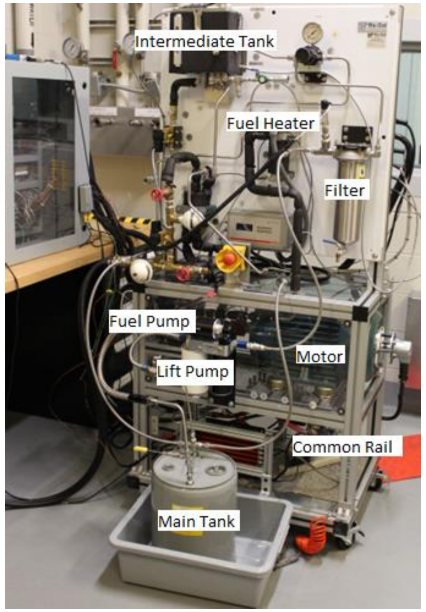
# PROCEDURE – DURABILITY EXPERIMENTS

## Procedure

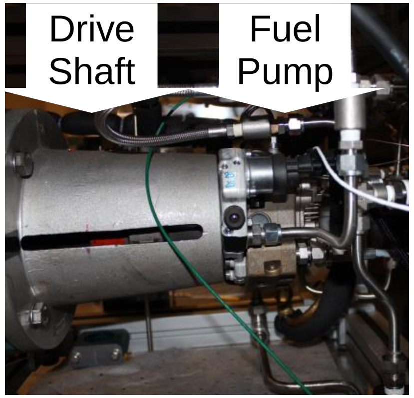
1. Break-in/Baseline operation with jet fuel for 24 Hours
2. Switch to test fuel
3. Operate until failure criteria
4. Characterize pump failure

## Fuels - Ethanol, Decane

| Controlled Variable | |
|---|---|
| Rotation Speed *Half of Engine RPM | 2000 RPM |
| Rail Pressure | 1400 bar |
| Output Flow | 770 mL/min |
| Input Fuel Temperature | 40 ºC |




Experimental Fuel Pump Stand




Fuel Pump mounted on stand

## Failure Criteria

- Low Pressure
- Low flow rate
- High low-pressure fuel return temperature
- High high-pressure fuel return temperature

## Important Sensors

- Acoustic Emission
- Embedded Pressure and Temperature Sensor
- Rotary Encoder
- Flow Meters
- Thermocouples
- Pressure Sensors

## Acoustic Emissions

- Detects high-frequency vibrations (50-500 kHz)
- Sensitive to tribological activity (wear, scuffing, etc.)

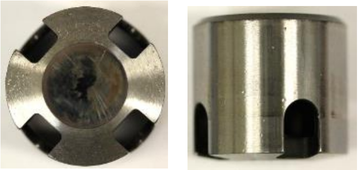
Acoustic Emission Sensor

# PUMP PERFORMANCE

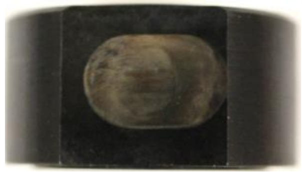
| Pump Lifetime (Hours) | | |
|---|---|---|
| **Test #** | **Ethanol** | **Decane** |
| 1 | 0.340 | 3.085 |
| 2 | 151.228 | 294.4 |
| 3 | 43.107 | |

- **Lifetime is low -** Pumps are design for 1000s hours.
- **Variance is high -** This is consistent with scuffing in other components

## New Pump



Bucket Tappet

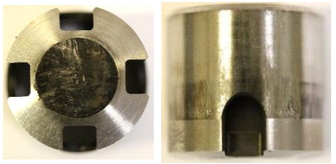


Cam-ring

## Decane

**Failure Criteria:** Exceeded maximum low-pressure fuel return temperature

**Root Cause:** Scuffing in cam-ring bucket interface



Bucket Tappet

Cam-ring

## Ethanol

**Failure Criteria:** Exceeded maximum low-pressure fuel return temperature

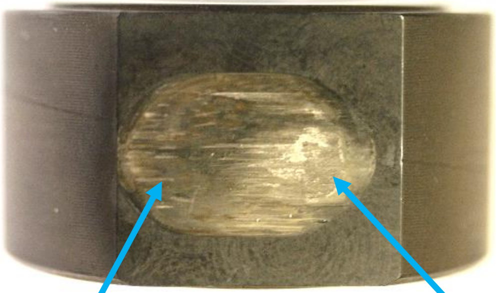
**Root Cause:** Scuffing in cam-ring bucket interface

Bucket Tappet

Cam-ring

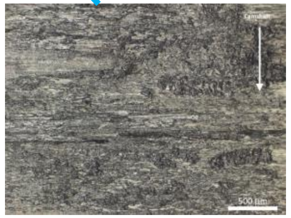
# FAILURE ANALYSIS - DECANE

Cam-ring



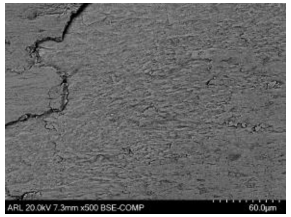
Side 2

Side 3



| Element | Mass Norm. [%] | Atom [%] |
|---|---|---|
| Iron | 91 | 73 |
| Carbon | 5.6 | 22 |
| Chromium | 1.6 | 1.4 |
| Oxygen | 1.4 | 4.0 |

BSE

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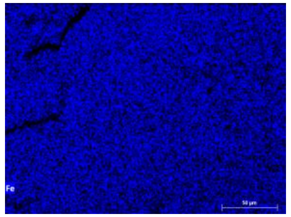

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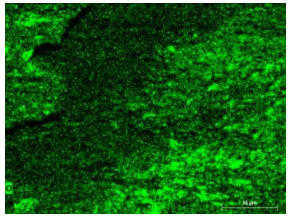
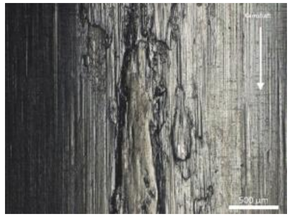


Bucket Tappet Top


1



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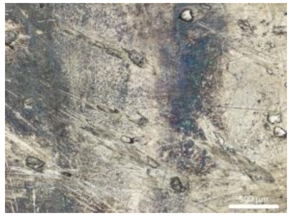


Scuffing of surface. Less severe than in Ethanol experiments

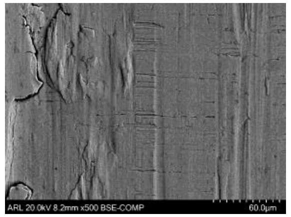
Severe scuffing concentrated on one side

Very little oxidation of surface

Bucket Tappet Side

| Element | Mass Norm. [%] | Atom [%] |
|---|---|---|
| Iron | 92 | 76 |
| Carbon | 5.3 | 20 |
| Chromium | 1.7 | 1.5 |
| Oxygen | 0.8 | 2.4 |

BSE

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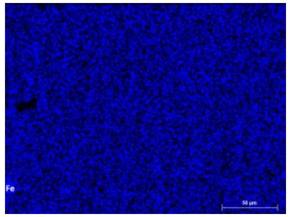

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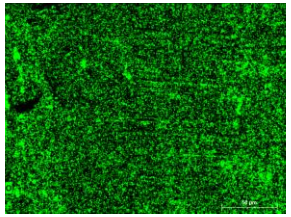
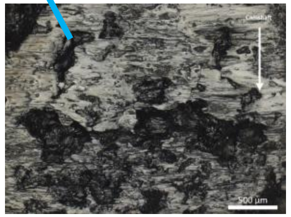


# FAILURE ANALYSIS - ETHANOL

Cam-ring

Side 2

Side 3



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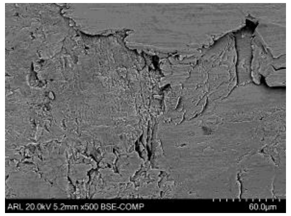

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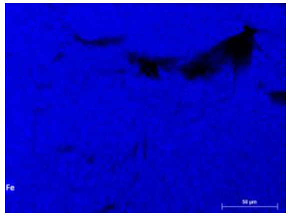

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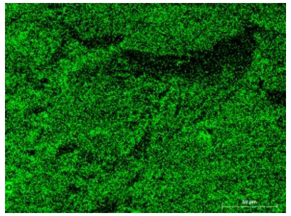

Bucket Tappet Top


1

2

Scuffing of surface. More severe than in Decane experiments

Severe scuffing concentrated on one side

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Bucket Tappet Side

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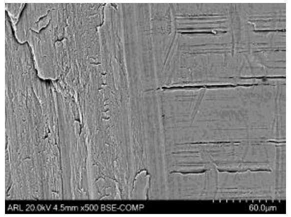

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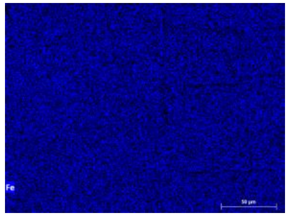

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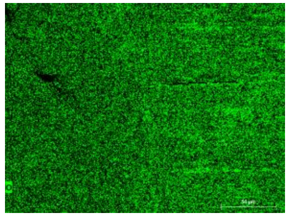


# APPROACH – SENSOR ANAYLSIS


**How does this work in practice?**

# DATA ACQUISITION – ACOUSTIC EMISSION

## Data Procedure

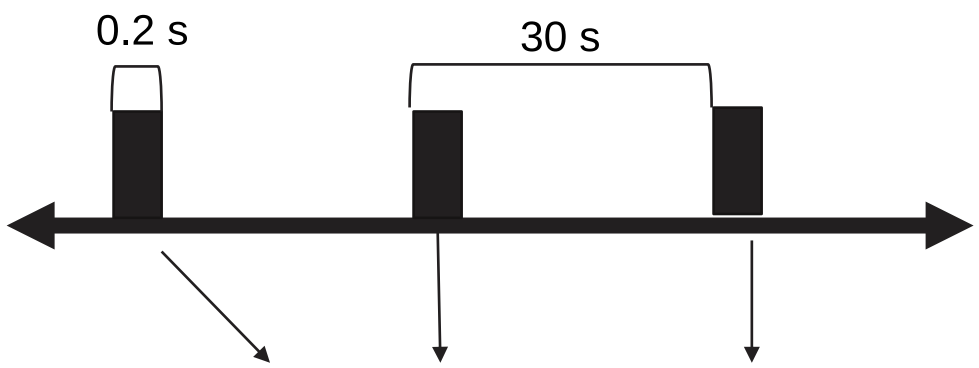
Data is collected in bursts

- -Acoustic Emission Intensity (V)
- -Angular Position

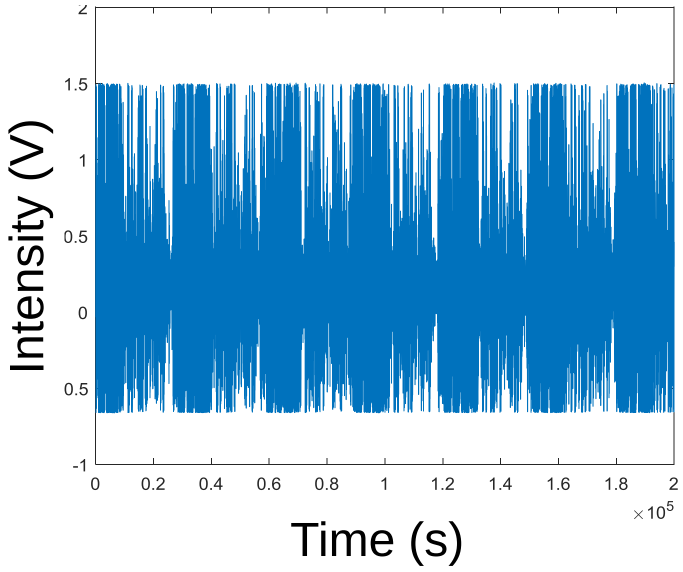
| | |
|---|---|
| **Burst Period** | **0.2 s** |
| **Burst Interval** | **30 s** |
| **Acquisition Rate** | **1 MHz** |
| **Nyquist Frequency** | **500 kHz** |
| **Frequency Range of Sensor** | **100 to 500 kHz** |

Acoustic Emission Sensor

What does the raw data look like?




**A single burst acquisition of acoustic intensity data**



# DATA PROCESSING

**<u>Continuous Wavelet Transform (CWT)</u>**

- Like Fourier Transform but uses Wavelets
- Signal intensity becomes function of time and frequency

Encoder Data of Single Burst

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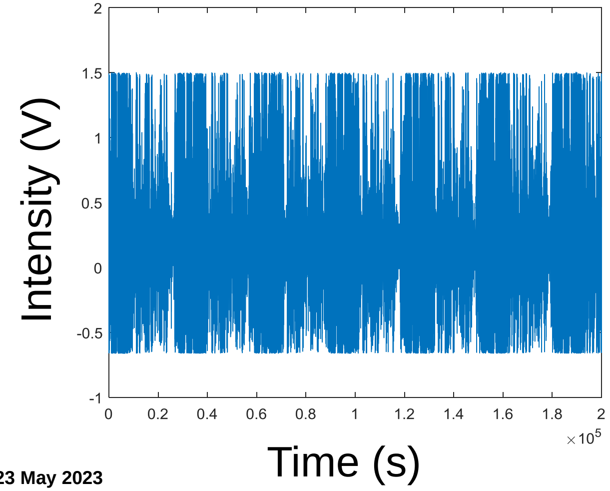
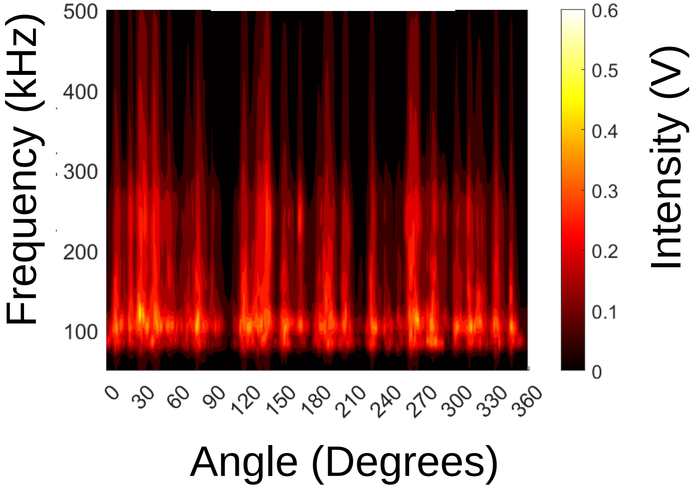
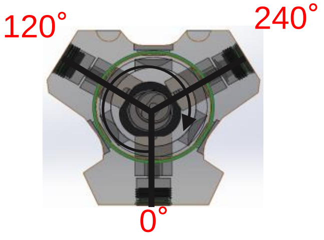
Raw Data of Single Burst Acquisition




CWT

Combined Position Correlated Time-Frequency Response

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Burst 2 Data

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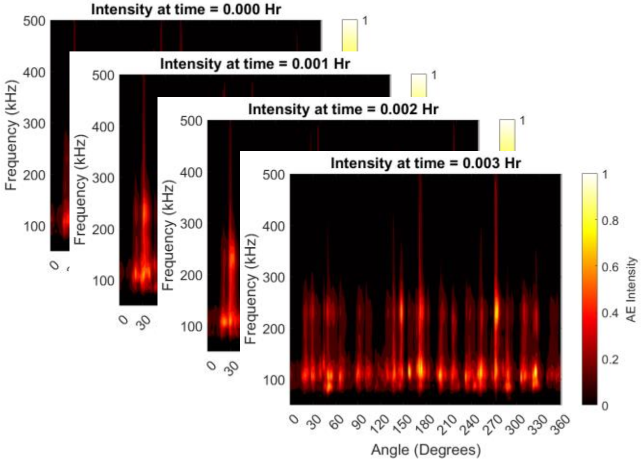
**Dataset for an entire experiment**

- Each point in time is represented by an image
- Each image shows intensity as a function of position and frequency



# CLASSIFY COMPONENT STATE

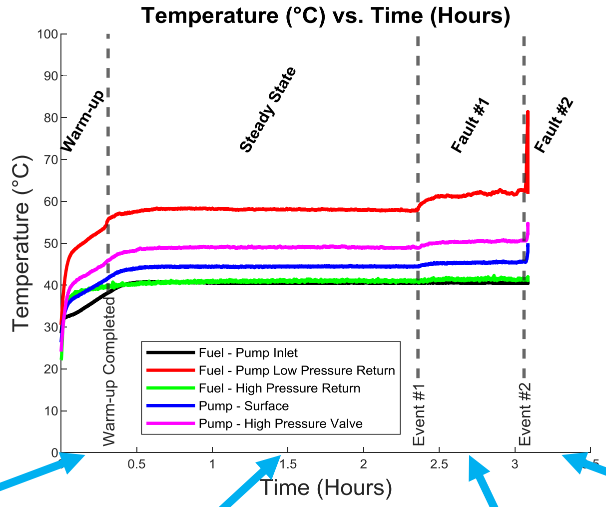
**Classification is possible.**

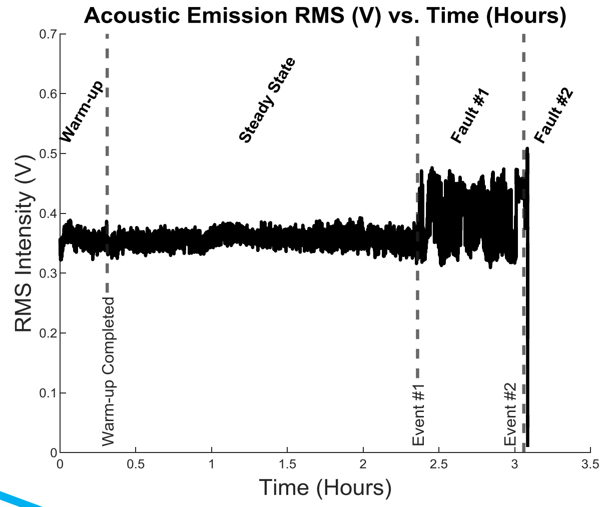
- The pump enters 4 states.
- Each state can be identified by a distinct pattern in the image data (processed acoustic data).

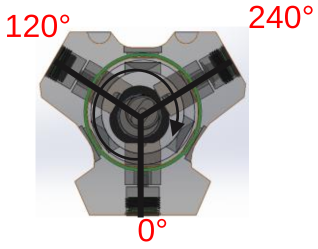
**Mechanism of failure - two set process:**

- Fault #1 - Initiation of damage due to scuffing on one cam-bucket interface
- Fault #2 - Propagation of damage to other sliding interfaces

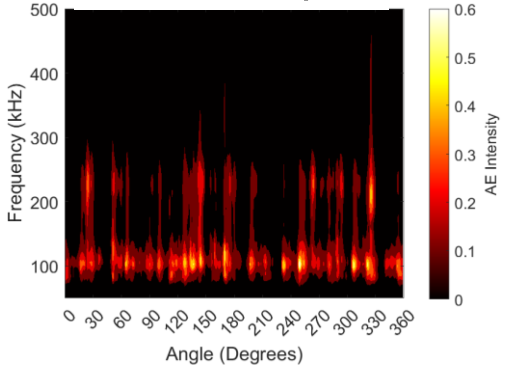
## Decane Test #1 Data



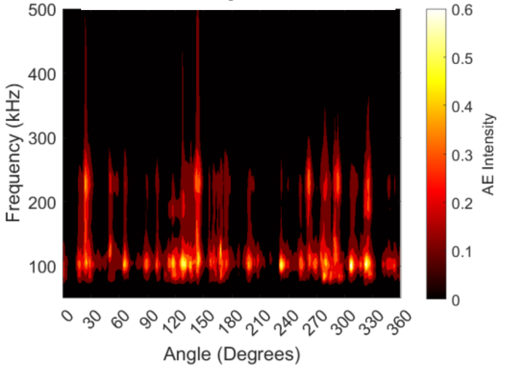



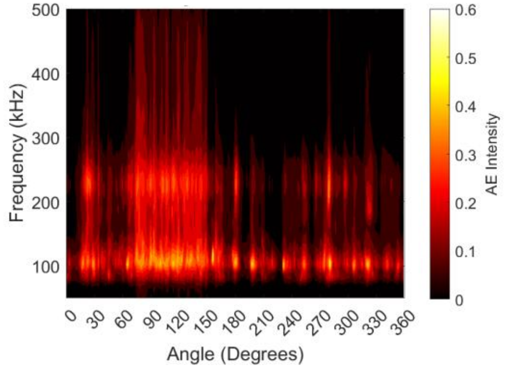

Warm Up



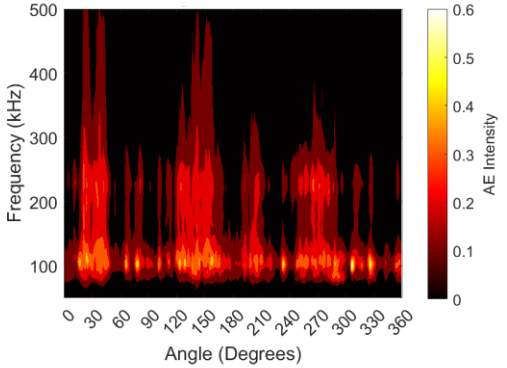

Steady State




Fault #1




Fault #2



# APPROACH

Sensor(s)

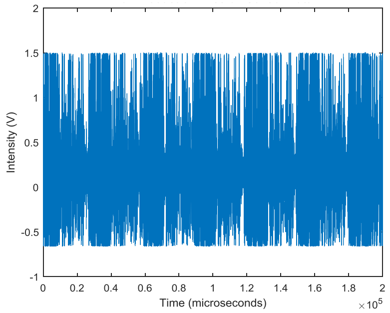
Component → Test → Raw Sensor Data → Process → Interpretable Performance Data → Classify → Component State → Maintenance

Sensor: Acoustic Emission

Component: High-Pressure Fuel Pump

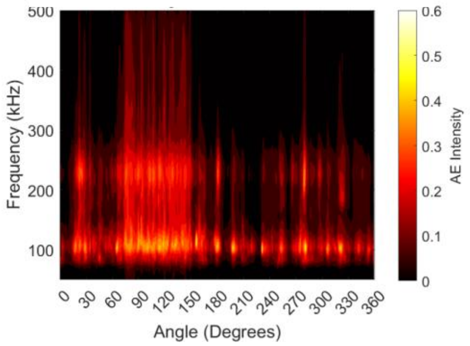
Raw Acoustic Emission

Intensity Data




Position-Frequency Correlated

Acoustic Emission Intensity Data




**Q: How can a machine classify complex data patterns?**

**A: Machine Learning**

# MACHINE LEARNING (ML) - BACKGROUND

## What does machine learning do?

Trains a model on known inputs and output to predict future outputs

## Steps to machine learning:

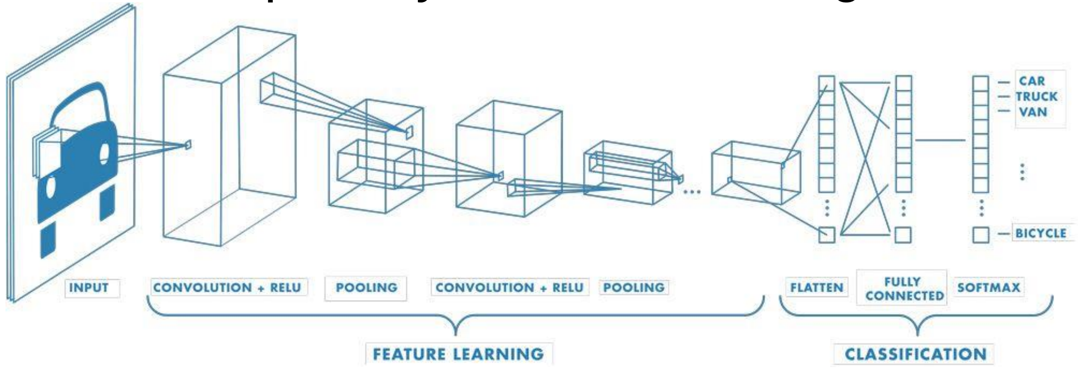
1. Collect Data
2. Sort Data
3. Train Model
4. Validate Model
5. Apply Model

## What ML methods do we use?

Convolutional Neural Networks (CNNs) with transfer learning

## Convolutional Neural Networks

- Neural Networks use a series of interconnected layers to isolate features and classify data
- CNNs are especially effective for image classification




Source: https://www.mathworks.com/discovery/convolutional-neural-network.html

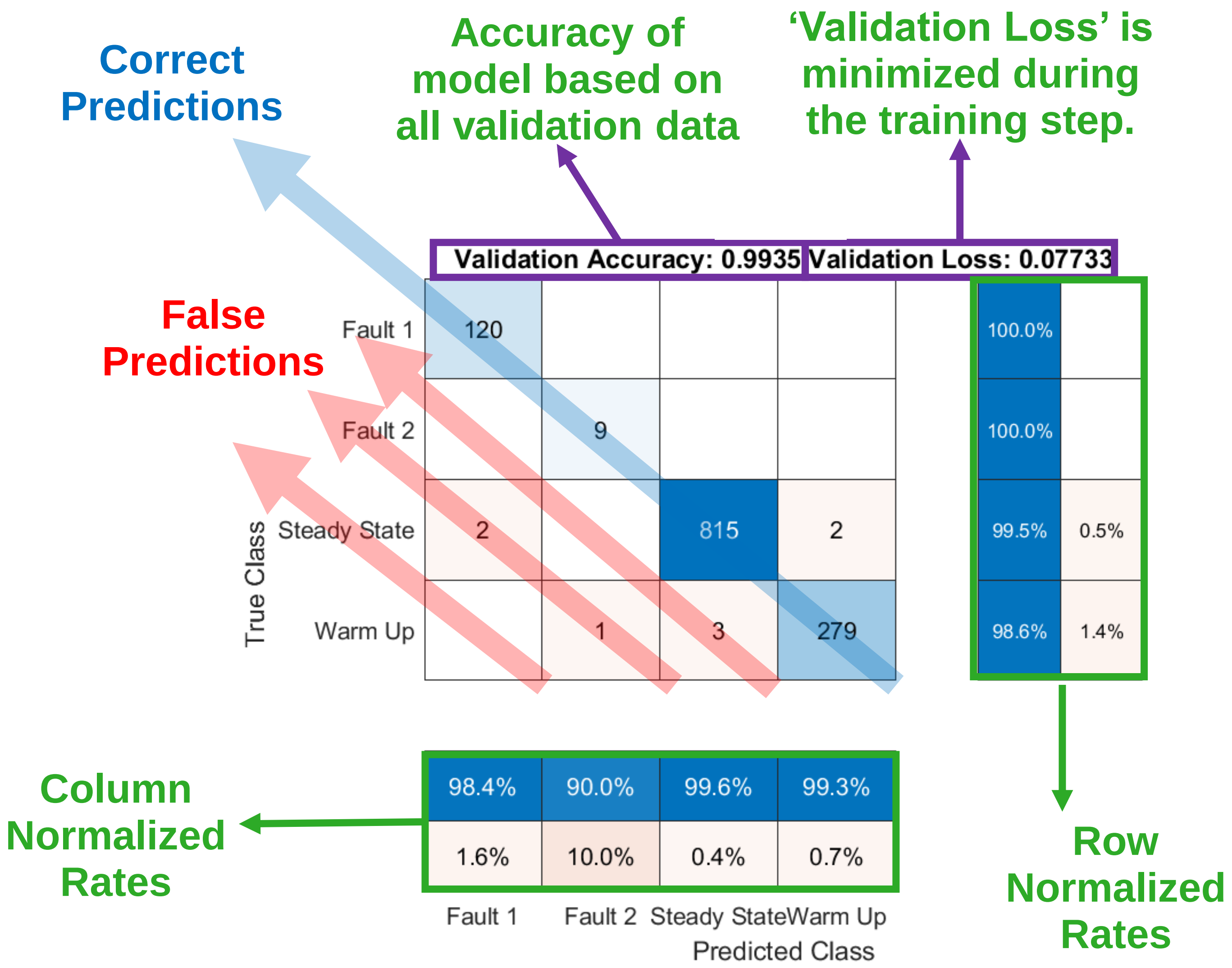
## Transfer Learning

- Transfer learning utilizes a previously trained model as a basis for feature identification for future models
- The last layer(s) are retrained on the new training data to adapt to new circumstances
- **We used an AlexNet trained on the ImageNet dataset as the base of our models**

# EVALUATING MODEL PERFORMANCE

**Confusion Matrix:**

- Commonly used in machine learning community
- Shows the predictions class vs. true class of a known validation dataset
- Correct predictions are on the central diagonal
- The accuracy of each row and column are shown beside the central matrix
- The confusion matrix is useful for understand when the frequency of false predictions and which states the model confuses.

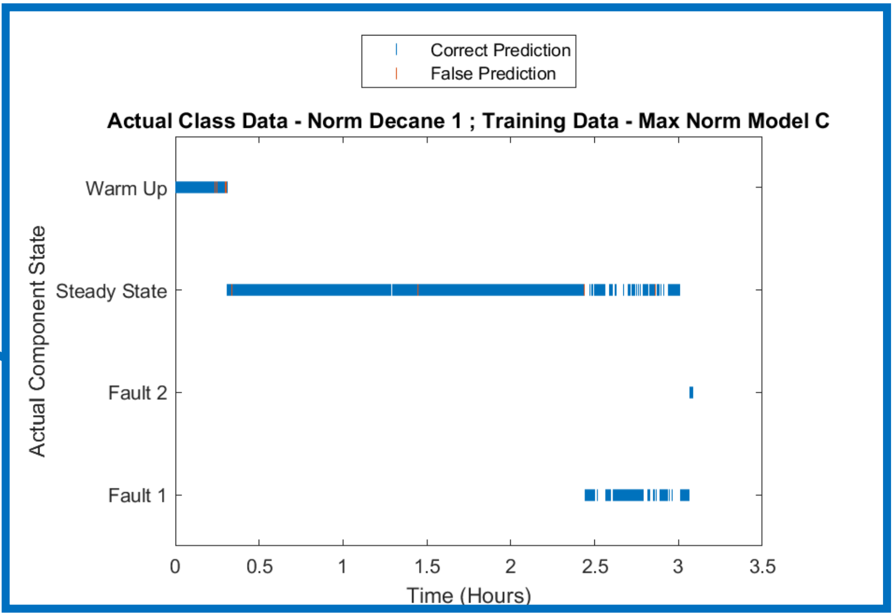


# EVALUATING MODEL PERFORMANCE

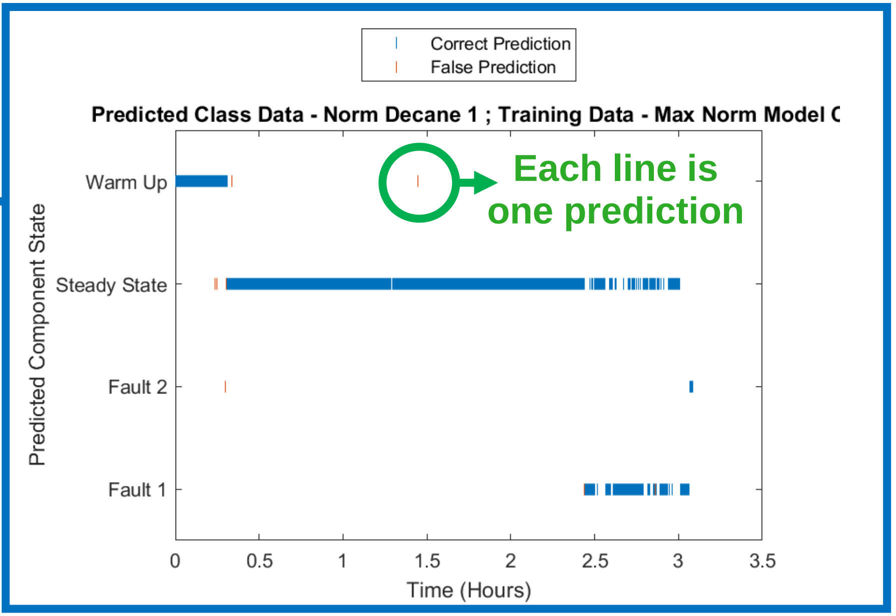
**Time-series predictions:**

- Displays the predicted state of each burst data acquisition (each point) vs. time
- False predictions are shown in red.
- We can see how the predicted state changes over the component life
- This visualization is useful for application of the model to new validation data
    - We can see when the state changes
    - Highlights when in time a model performs poorly

**True/Actual Class vs. Time**




**Predicted Class vs. Time**



# MODEL PERFORMANCE

**How much data is needed to train the model?**

- A model was trained with 10% of the decane dataset
- Validation was completed on both the full decane and full ethanol datasets

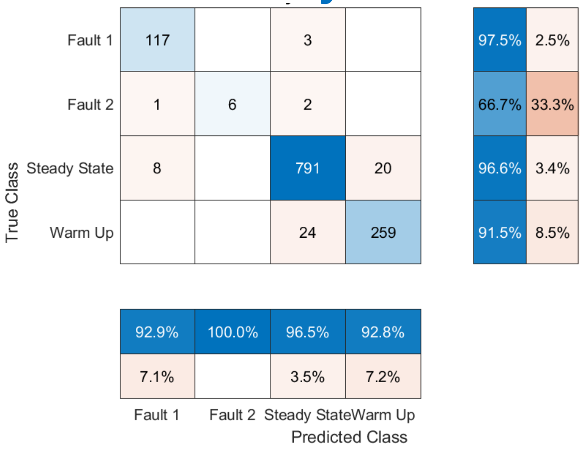
**Results:**

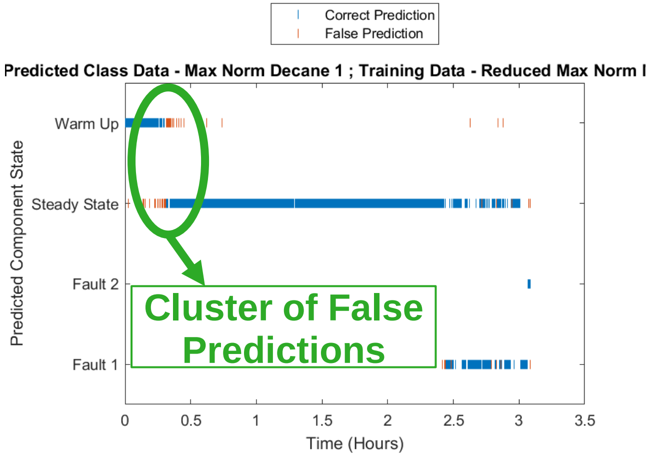
- The model performed with comparable accuracy to the model trained with the full decane dataset
- False predictions are more common during transitory periods
- The model performs poorly when applied to the ethanol test data

**We need to train with more diverse data if we want the model to be more adaptable.**

## Validation w/ Decane

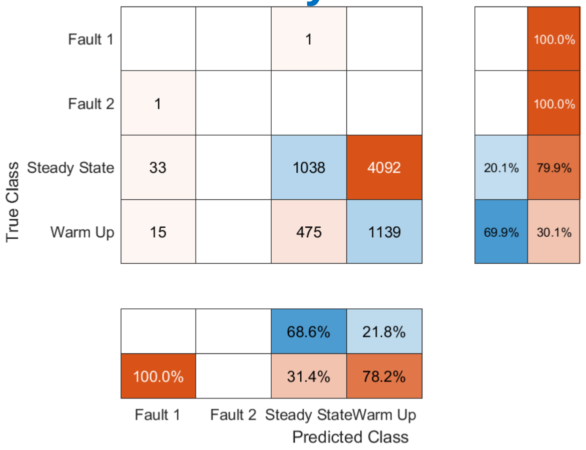
**Total Validation Accuracy = 95.3%**

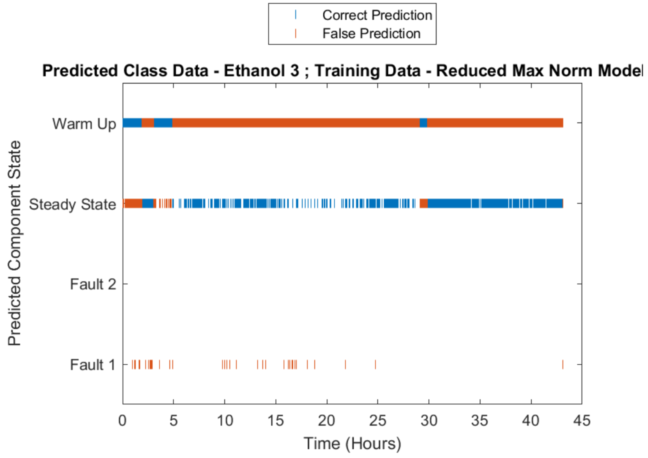



## Validiation w/ Ethanol

**Total Validation Accuracy = 32.0%**



# CONCLUSIONS

**Conclusions:**

- **Pump lifetime with low-viscosity fuels is low (<300 Hrs) and has high variance.**
- **The pumps failed due to scuffing of the camring-bucket interface**
  - Scuffing was non-oxidate
- **Failure followed a two-step process**
  - First initiation of scuffing on a single camring-bucket surface
  - Second propagation of damage to other interfaces in the pump
- **We defined an approach to determine a components state**
  - Acquire acoustic emission data
  - Process the data using wavelet analysis
  - Classify the data into states using CNNs
- **A diverse dataset is necessary to improve the adaptability of models to new situations**

**Path Forward:**

1. Continue to the explore limits of the AE approach (Where does it work?, When does it not?)
2. Collect data to improve diversity of training dataset
3. Modify pump materials to improve performance

# THANK YOU.