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Fault Detection in the Solvent Extraction Process with Non-traditional Sensors

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Changing the World's Energy Future

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Idaho National Laboratory

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Introduction

Solvent extraction is used to separate metals or other complexes into two different immiscible liquids and is an essential component of the PUREX Process. Improvements to the solvent extraction process can directly contribute to an organization's ability to ensure the purity and recovery of special nuclear materials from spent nuclear fuel. Such improvements can benefit nuclear reprocessing efforts, increase fuel reutilization, and limit the concentration of actinides in nuclear waste repositories.

Figure 1. Annular centrifugal contactor array for solvent extraction. The apparatus contains 30 contactors in total, with 8 accelerometers placed on or near the contactors.

Motivation

The goal of this project is to endow process operators with the ability to monitor the solvent extraction process in real time.

- Due to the lack of a stateful system, testbed operators are forced to spend valuable time and resources analyzing the results of campaigns irrespective of the experiment's success.
- Through the employment of machine learning, this project aims to use non-traditional sensors that record vibrational, acoustic, and seismic data to create an economical method for detecting faults in the solvent extraction process.

Data Preprocessing

Data Migration → Downsampling → Data Annotation → Data Cleansing

- Downsampled original signal from 12800 Hz to 320 Hz to optimize the processing speeds.
  - Resultant loss of resolution is not expected to diminish feature prominence in the accelerometer signals.
- Sensor data is converted from mV to the relevant unit being measured (mV to g for accelerometers).
- Data entries recorded during the flood event are marked based on the start and end of the anomaly window observed during the solvent extraction campaign (as highlighted in the Raw Data plot below).

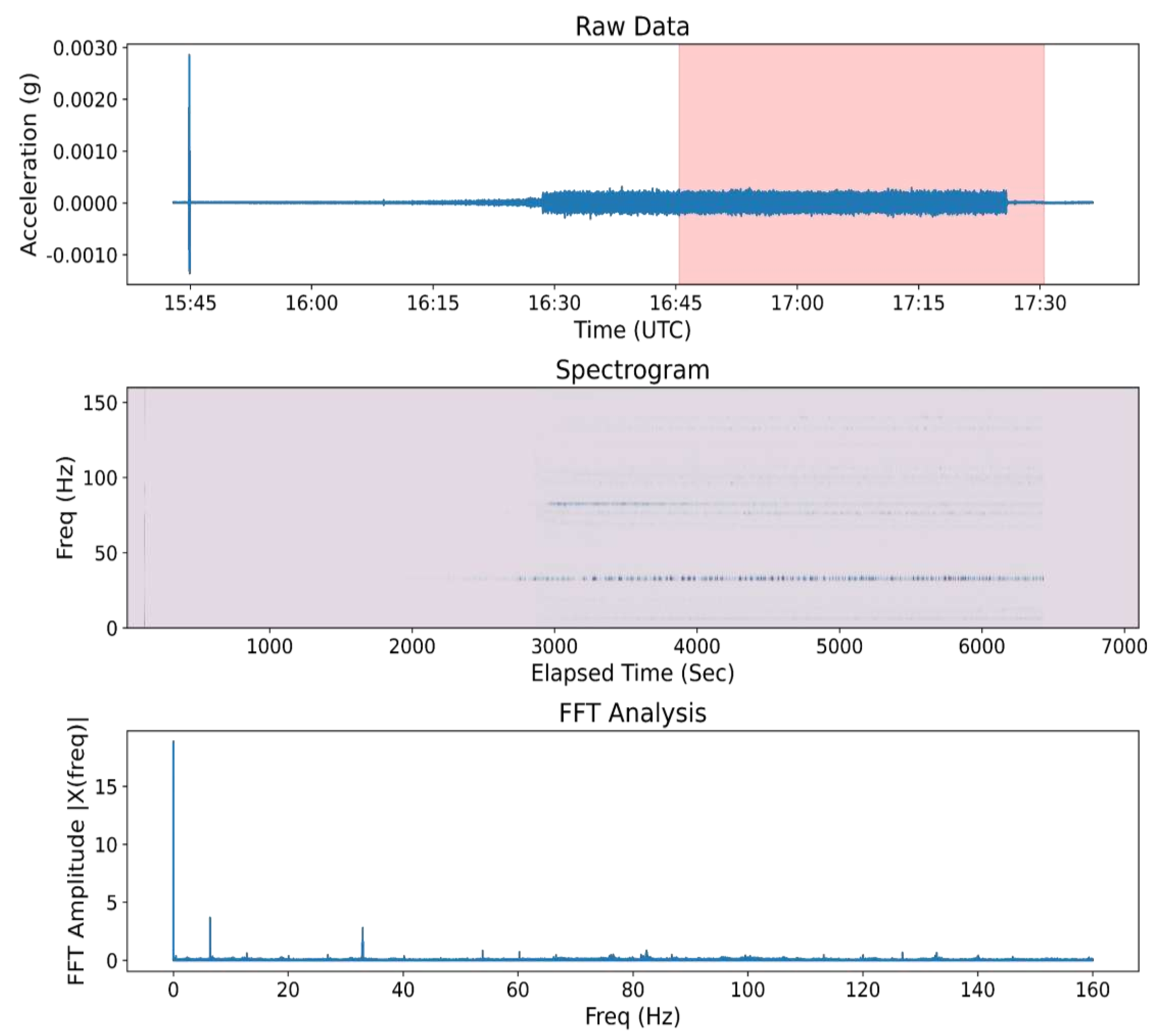

Figure 2. Raw data, spectrogram, and Fast-Fourier Transform Analysis plots for an accelerometer that monitored the Contactor 10 motor during a solvent extraction campaign.

Model Selection

This problem domain necessitates a model capable of leveraging data from 8 vibrational sensors and will progressively incorporate various other data input streams from acoustic and infrasound sensors.

- Support Vector Machines (SVMs) are particularly advantageous in high-dimensional problem spaces where binary classification is employed.
- Long Short-Term Memory (LSTM) models are a form of recurrent neural network (RNN) adept at handling sequential data. In the context of this project, the sequential data used for model training can benefit from the model's capacity to capture the temporal dynamics of the experiment over time.

Evaluation

The SVM and LSTM models will be evaluated using time-based cross-validation to ensure a robust performance assessment. Time Series respects the temporal nature of the data by preserving the order of the observations during the cross-validation process. After cross-validation, the SVM and LSTM models will be compared for estimated performance.

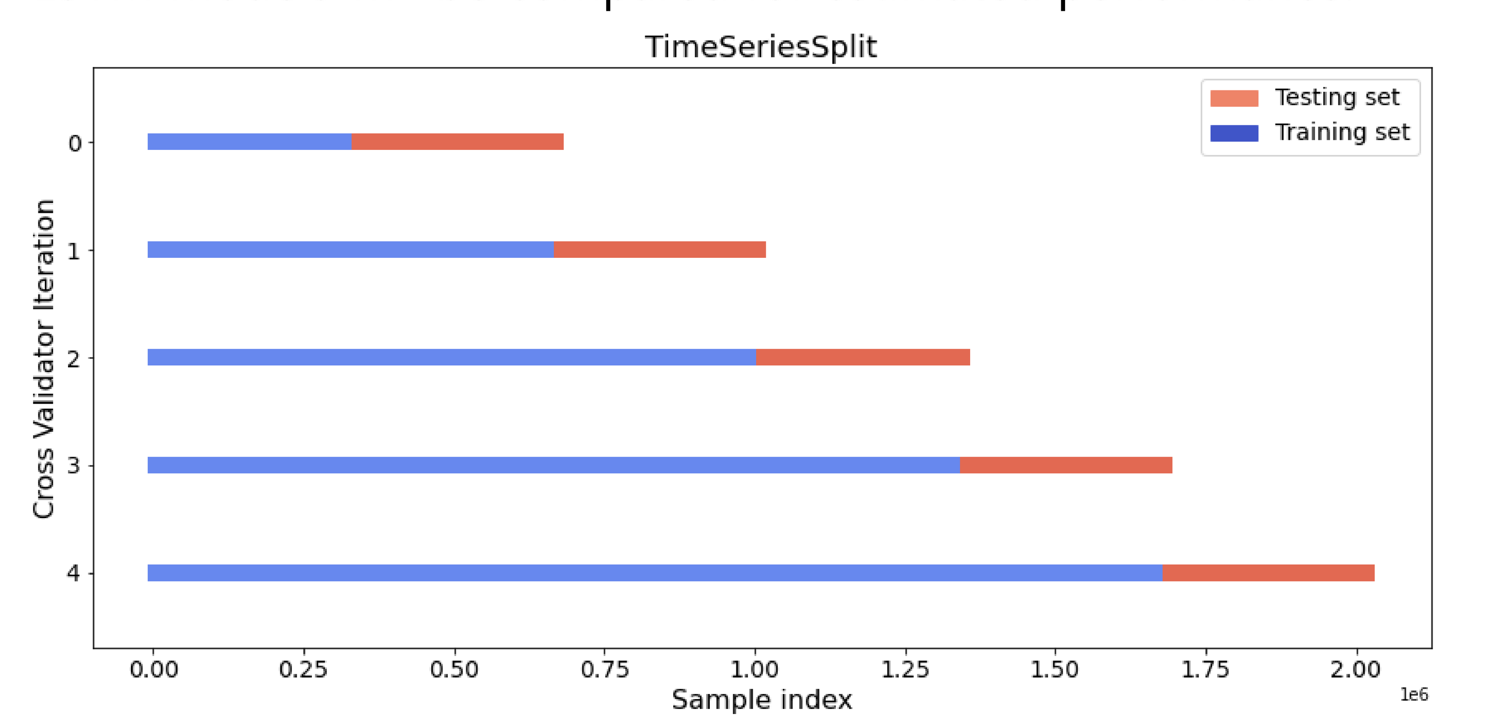

Figure 3. A visualization of the splits for each fold generated by a Time Series cross-validator. Subsequent training sets are always supersets of the previously generated training sets.

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