# Rapid IR Fuel Screening Project 25

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#### **Project 25**

### **Rapid IR Fuel Screening**

#### **Stanford University**

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Cost Share Partner(s): Stanford University

#### **Objective:**

Develop a **compact, low-volume prescreening tool** for the prediction of physical and chemical properties of sustainable aviation fuels (SAFs) using Fourier-Transform Infrared (FTIR) spectrometry and advanced statistical analysis methods.

#### **Project Benefits:**

- The FTIR prescreening approach will make the SAF design and approval process less costly and more efficient
- This low-volume (<1 mL) method yields insights that are complementary to other prescreening approaches (e.g., GCxGC).

#### **Research Approach:**

- Develop regularized linear and non-linear models that correlate the physical, chemical, and combustion properties of a fuel (e.g., boiling point, heat of combustion, flash point, etc.) with its vaporphase, 2-15 µm FTIR absorption spectrum.
- Apply these models to predict physical and chemical properties of next-generation SAFs and fuel components.

#### **Major Accomplishments (to date):**

- Measured spectra of 38 World Jet Fuel Survey (WJFS) samples and predicted molecular weights
- Including WJFS samples in training set improves model performance for similar fuels
- Implemented facility improvements and began preliminary measurements of liquid-phase spectra

#### **Future Work / Schedule:**

- Begin preliminary measurements for combined liquid- and vaporphase training set
- Determine effect of phase on the performance of property prediction models
- Develop a combined liquid-vapor model

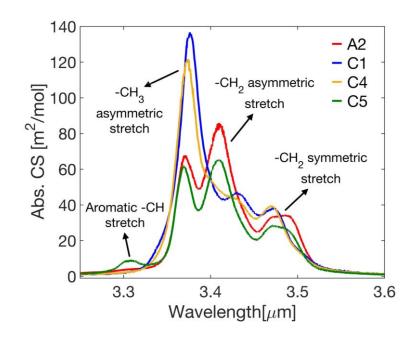
### **Introduction**

#### **Concept**

- The vapor-phase IR absorption spectrum of a hydrocarbon fuel contains quantitative information about molecular structure and functional groups
- Statistical models can be used to infer the physical and chemical properties of fuels from this spectral information



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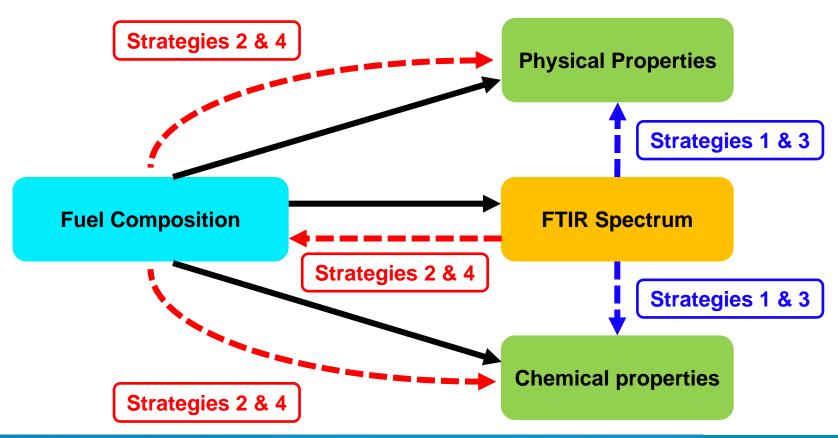
Fuel structure is evident in the IR spectra; the location and magnitude of absorption features reflect the type and number of functional groups, and can be correlated with physical/chemical properties





### Broad categories of spectral analysis strategies

- Spectrum-Property Correlation Models Strategies 1 (linear) & 3 (non-linear)
- Spectrum-Composition Models Strategy 2 (Functional groups)
  Strategy 4 (Molecular species)







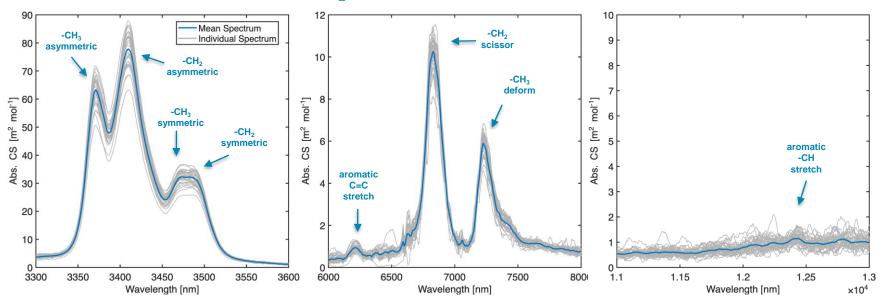
### **Past and Current Work**

- ✓ Compared FTIR-based approaches with alternative methods in literature, revealing comparable performance
- ✓ Successfully predicted the temperature-dependent thermodynamic properties for distillate fuels
- ✓ Implemented facility improvements to allow for higher temperature and extended wavelength measurements

> The following slides will focus on our recent progress analyzing model performance on 38 WJFS samples, training dataset populations, and preliminary comparison of vapor- and liquid-phase spectra



### FTIR Spectra of WJFS Samples



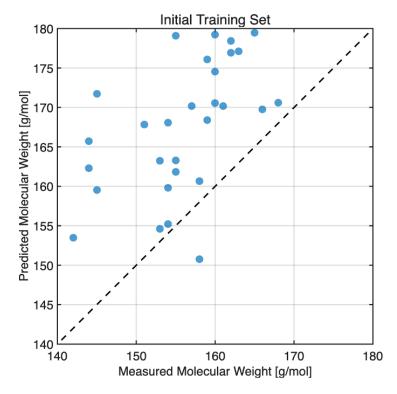
- 38 WJFS samples were measured in the vapor-phase
- Spectral variations prominent 3 and 7 μm regions
- Differences in spectra reveal functional group and compositional variation
  - Indicates opportunity for machine learning model to relate spectral variability to property variability

First application: Prediction of molecular weight...





## **Prediction of WJFS Molecular Weights**



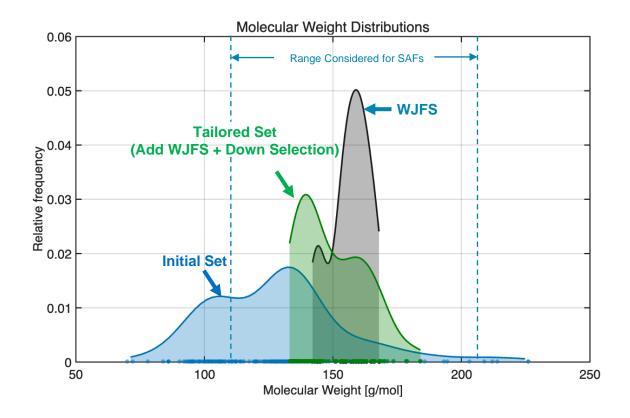
- Initial training set was developed for wide range of hydrocarbons and blends, but included only 8 conventional jet fuels
- Strategy 1 was trained on this limited set and applied to the 38 WJFS samples
- Overpredicts molecular weight with a Mean Absolute Error of 15.86 g/mol
- Why: Training set lacks sufficient number of samples with properties closely resembling conventional jet fuel!

**Solution:** Improve training set by incorporating more conventional fuels!





## **Analysis of Training Dataset Population**



- WJFS samples show a relatively narrow distribution of molecular weight
- Initial training set spans a wider range and dips near the WJFS peak region
- Tailored set yields distribution that better represents conventional jet fuels

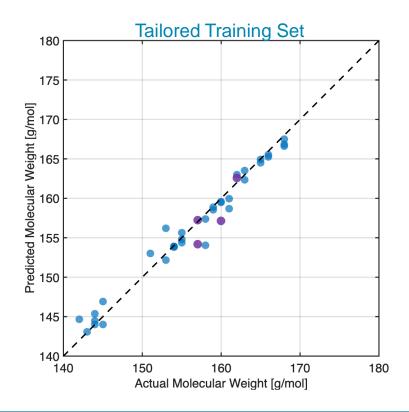
Emphasizes the need for a training set that reflects the target fuel types

Our broad dataset enables down-selection for tailored model development





## **Prediction of WJFS Molecular Weights**



Size and distribution of the training set are critical for performance.

Performance improves with a larger, relevant training set.

- 34 WJFS samples were added to initial set then the total set was down-selected to molecular weight range of 135-185 g/mol
- This tailored training set better aligns with conventional fuel range while preserving a robust sample size (total of 120 spectra)
- 4 WJFS samples kept out of training process to simulate performance on future Jet-A samples
- Tailored model yields improved predictive performance with MAE of 0.9 g/mol for tailored training set and 1.6 g/mol for the test set





## **Prediction of WJFS Molecular Weights**

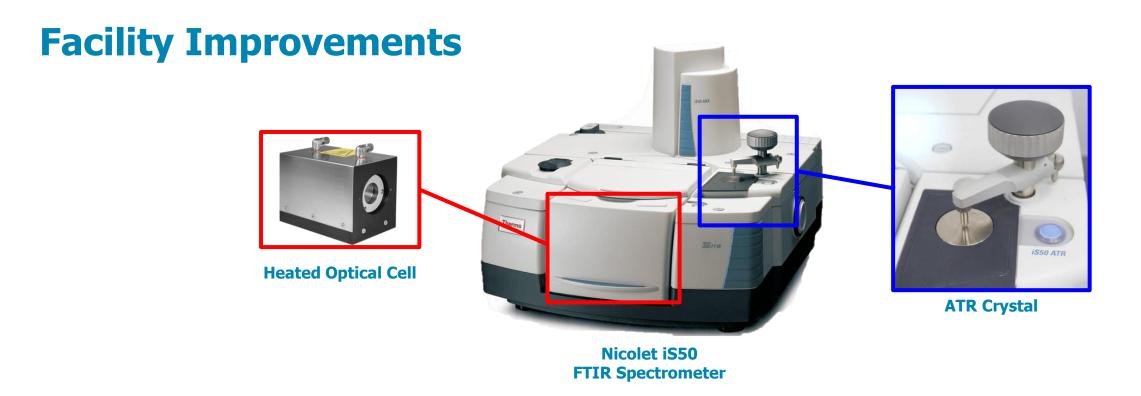
#### **Conclusions**

- Strategy 1 with limited initial training set overpredicts molecular weight of WJFS samples
- Adding WJFS samples and tailoring training set enhances model performance on conventional fuels
- Future work should expand and learn to tailor training sets for different fuel types

**Next:** Facility Improvements...





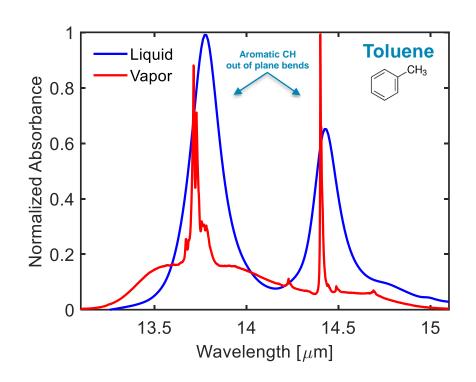


- Nicolet iS50 allows for expanded spectral range (1-200 μm), higher SNR, and better purge control and measurement of both vapor and liquid-phase
  - Heated optical cell allows for vapor-phase measurements at temperatures up to 300°C
  - ATR crystal cell used for measurement of liquid-phase samples





### **Comparison of Vapor and Liquid Spectra**



#### Vapor-phase spectra

- Exhibit well-resolved fine features and follow straightforward mixing rules
- Useful for inferring composition

#### Liquid-phase spectra

- Exhibit broader, shifted bands
- Potentially useful for the inferring properties influenced by non-linear or intermolecular effects

Can we combine data for improved performance?





## **Comparison of Vapor and Liquid Spectra**

### **Next Steps**

- Compile a training set containing both vapor and liquid-phase spectra for each sample
- Determine effect of phase on the performance of property prediction models
- Develop a combined liquid-vapor model to achieve optimal performance for all properties



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