On-Board Fuel Sensing for UAS and Ground Vehicle Applications

Dev B. Patel[1], Ashish Sutar[1], Abhinav Abraham[1], Dhananjay Ambre[1], Haruna Okada[2], Jacob M. Stafford[2], Niranjan Miganakallu[2], Eric Mayhew[3], Kenneth S. Kim[3], Scott Sanders[2], David Rothamer[2], Kenneth Brezinsky[1], Patrick T. Lynch[1]

[1]University of Illinois Chicago
[2]University of Wisconsin Madison
[3]US Army DEVCOM Army Research Laboratory

Motivation for UAS & Other Applications

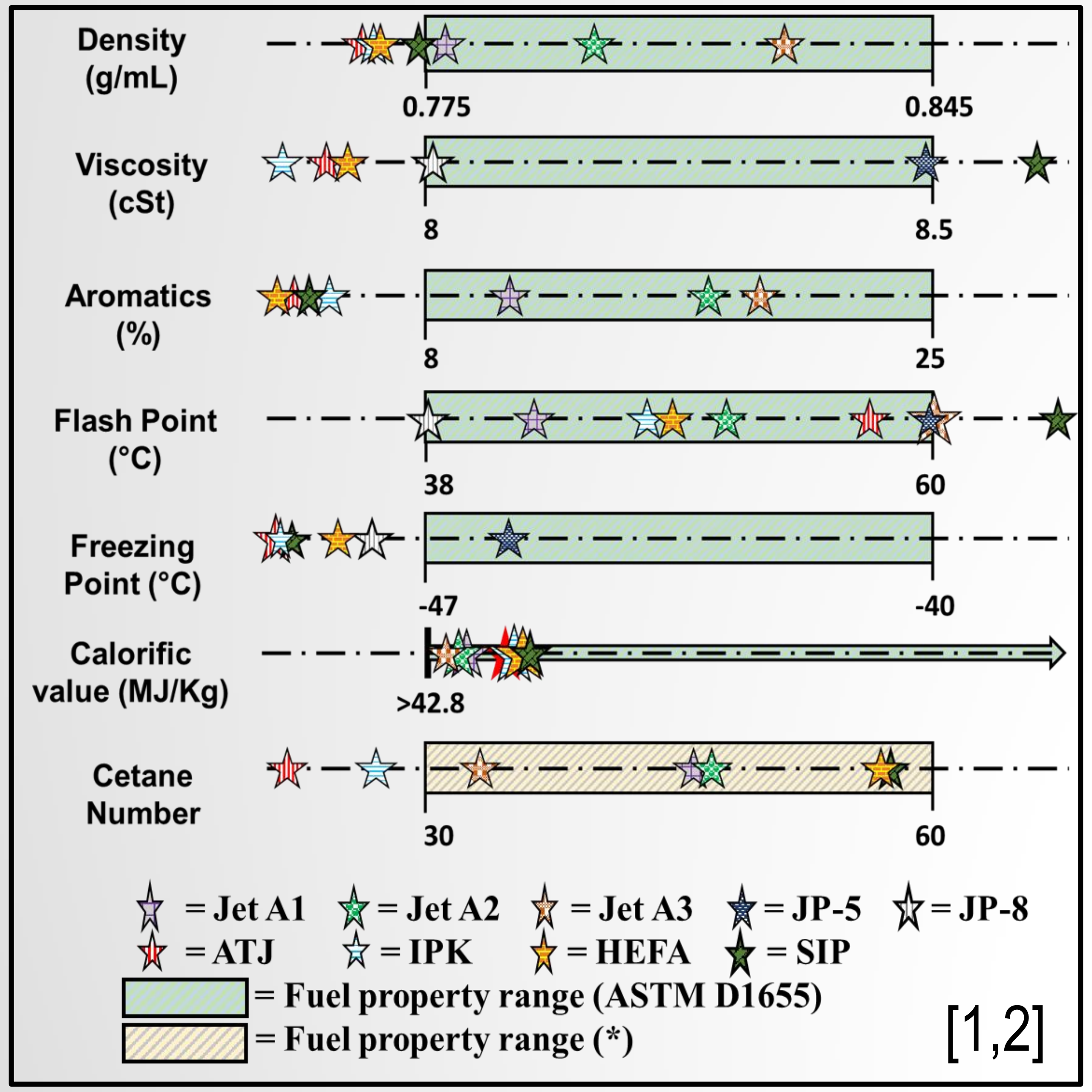
Fuels

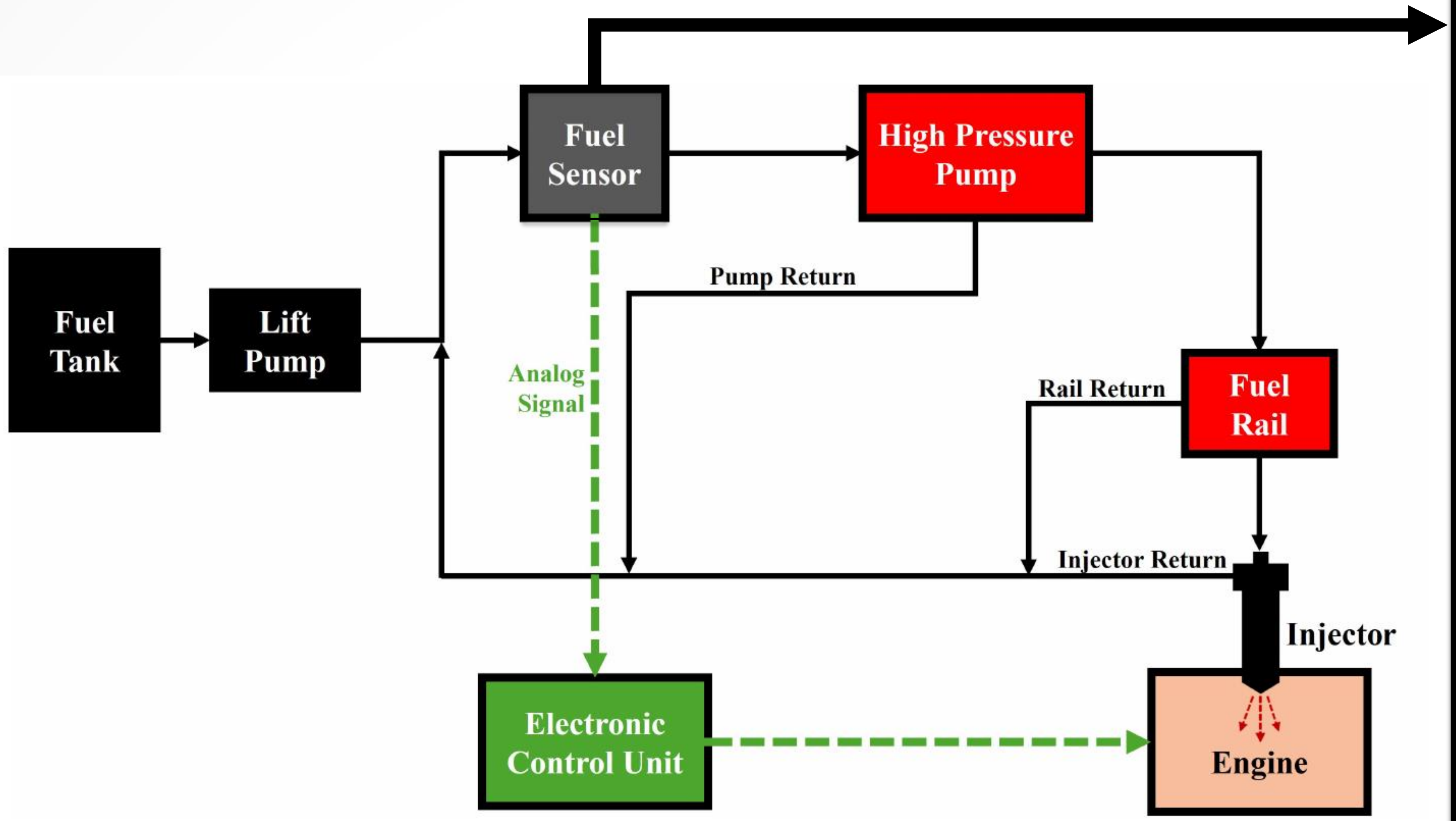
Conventional	Alternative
• Diesel	• Biodiesel
• Gasoline	• Ethanol
• Kerosene	• SAF

Jet fuels (conventional & alternative) exhibit wide range of fuel properties

Enable multi-fuel capable CI engines

- Ability to perform on-board inline fuel property determination

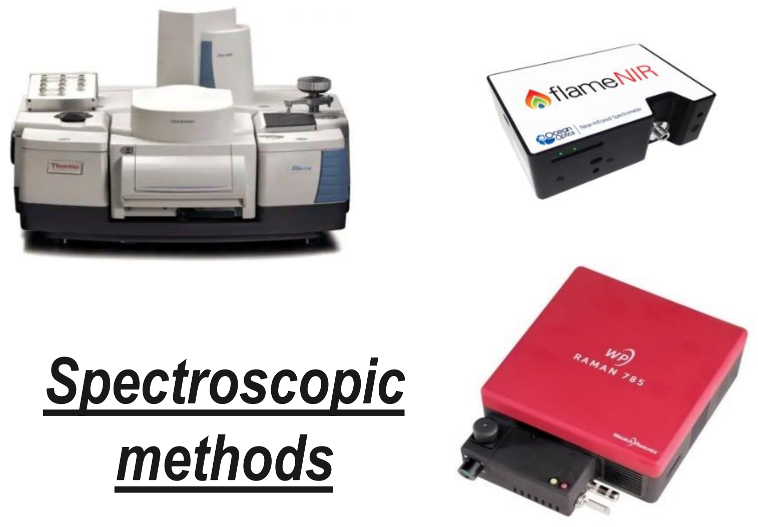




Conventional methods

- Incapable of simultaneous measurements
- Large and heavy
- Long response time
- Consumes substantial fuel
- Requires human intervention

Spectroscopic methods



- Capable of simultaneous measurement
- Onboard real-time estimation
- Can be miniaturized
- Quick response time
- No fuel consumption

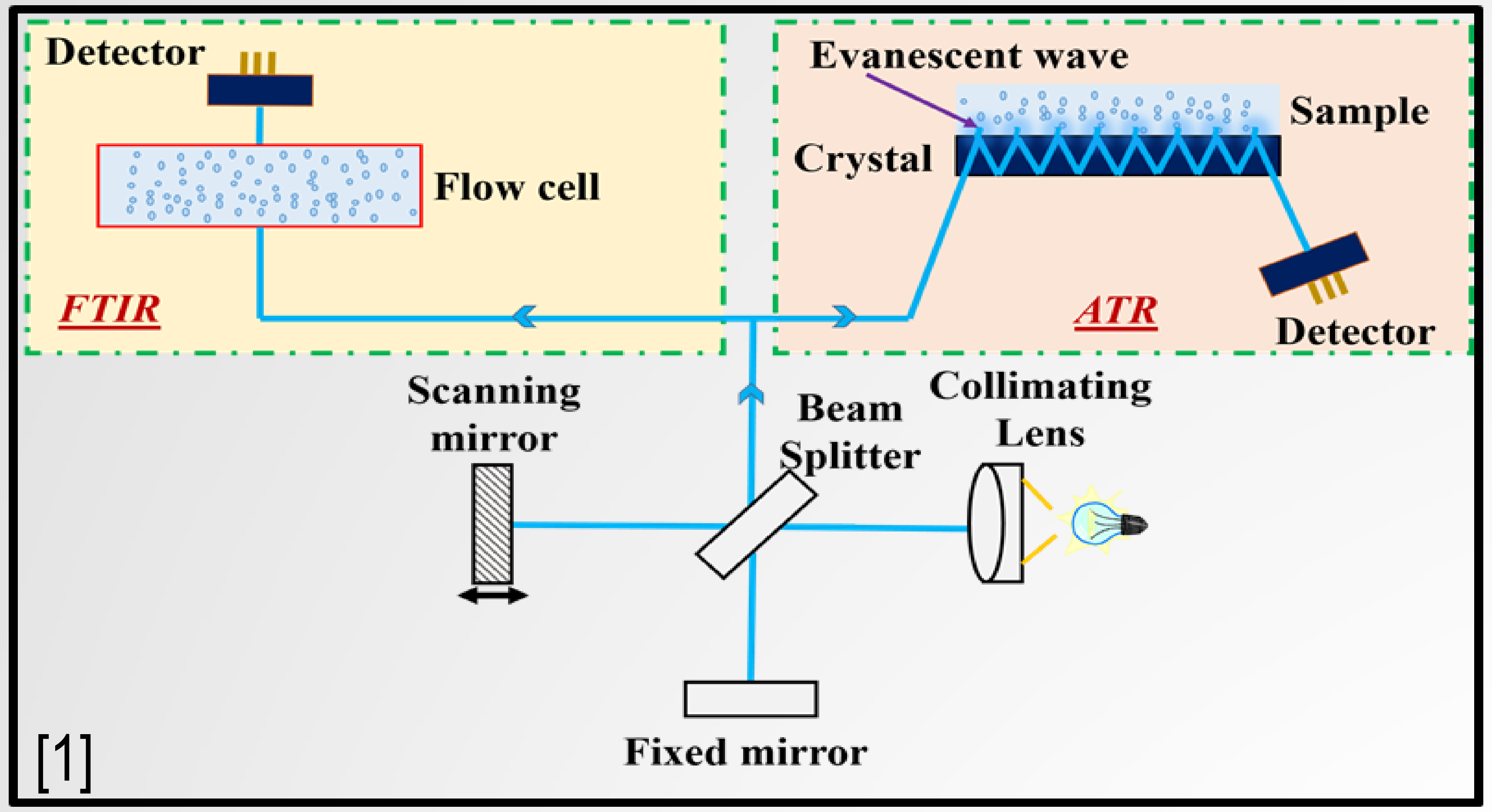
1) J.M. Bramer, J. Schmitigal, Evaluation of Cetane Improver Additive in Alternative Jet Fuel Blends, 2016.
2) T. Edwards, Reference jet fuels for combustion testing, AIAA SciTech Forum - 55th AIAA Aerosp. Sci. Meet. (2017) 1–58.

Fuel Sensing Methodology & Background

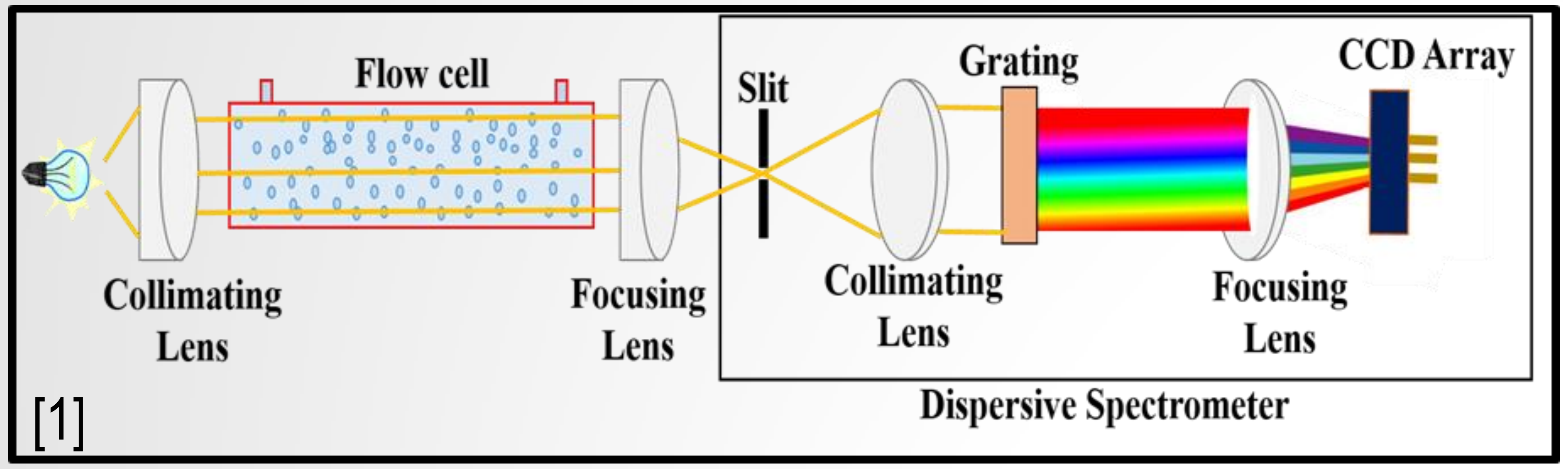
POWER & MOBILITY

Spectroscopic Techniques

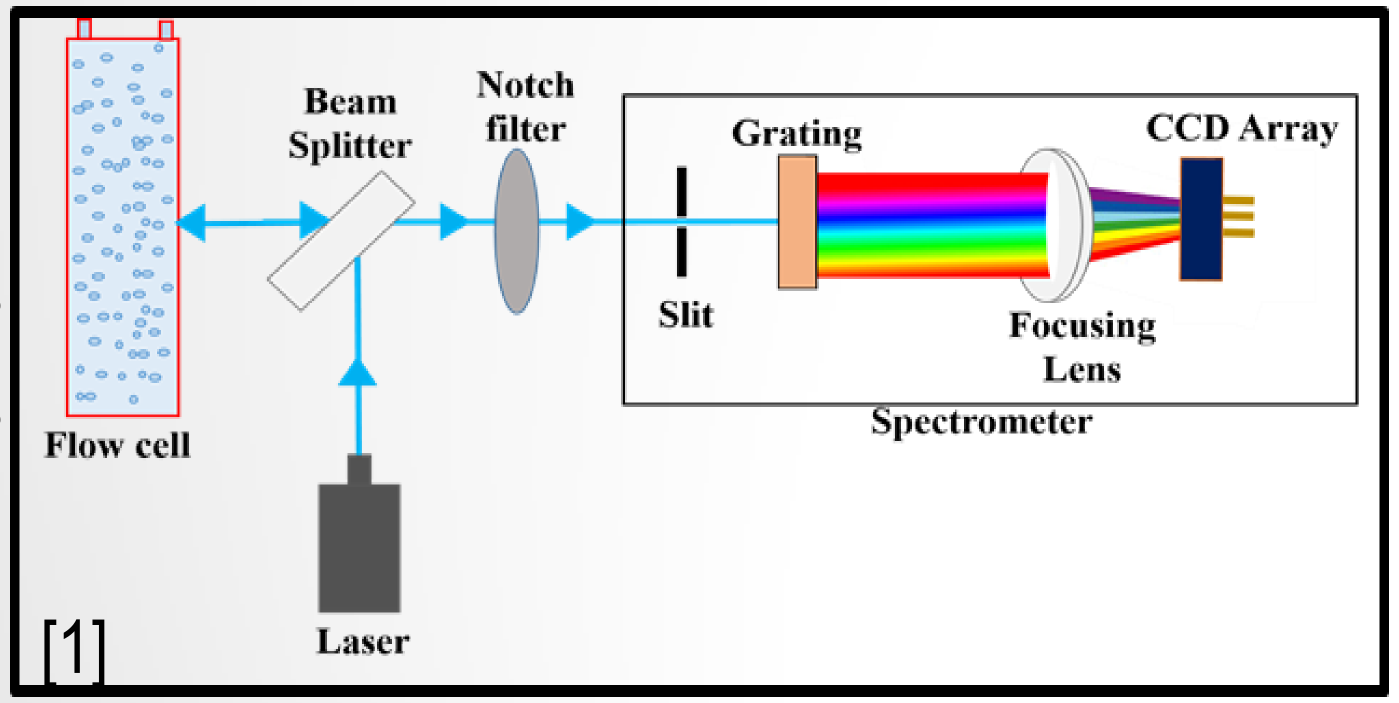
FT-ATR



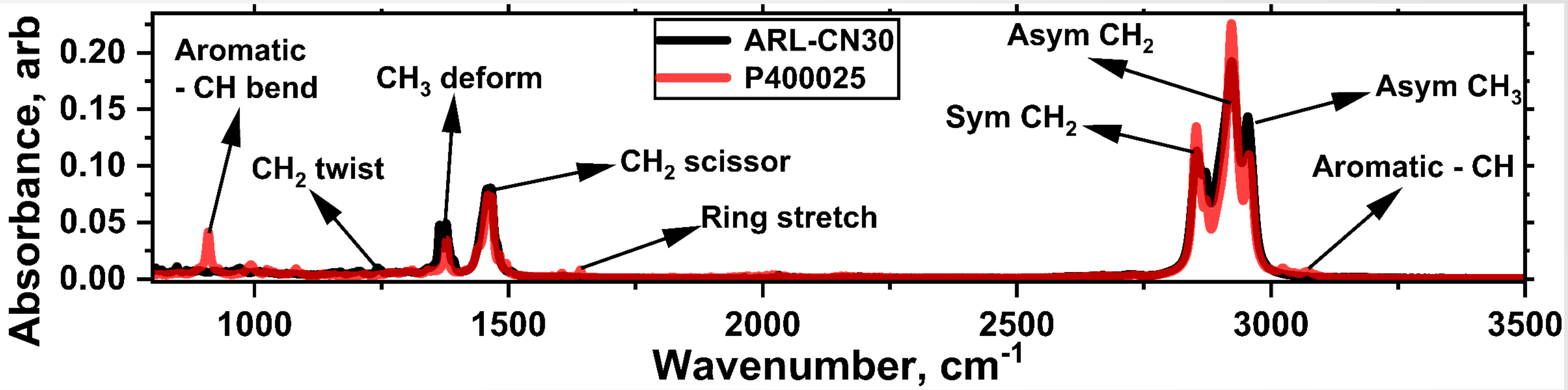
Dispersive NIR



Raman



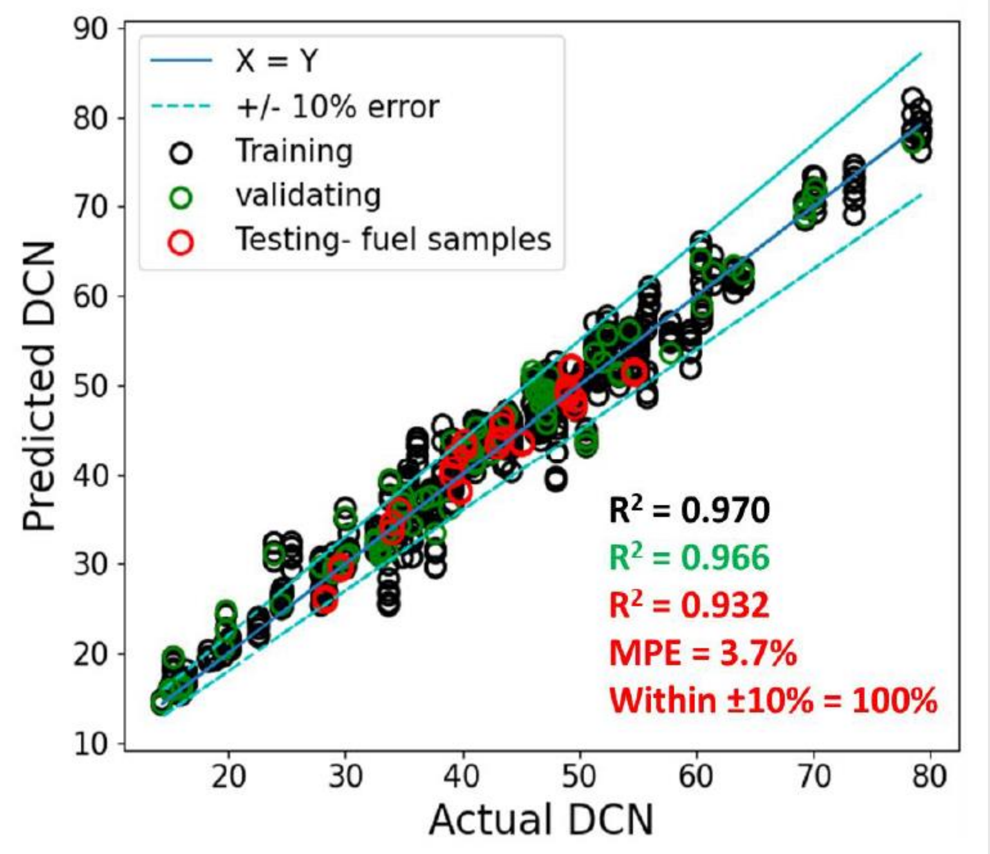
Spectral Data to Fuel Properties using Machine Learning



Spectra to fuel properties studies completed on DCN [2], viscosity [3], lubricity [3] and freezing point [3].

Fuel property predictive capabilities depend on:

- Spectral range and resolution
- Dataset used to train ML models



[2]

1) Abhinav Abraham, Dev Patel, Anandvinod Dalmiya, Ashish Sutar, Haruna Okada, Dhananjay Ambre, Manaf Sheyyab, Kenneth Brezinsky, Scott Sanders and Patrick T. Lynch. "Characteristics of Onboard Sensors for Fuel Ignition Performance," AIAA 2024-1244. *AIAA SCITECH 2024 Forum*. January 2024.
2) Dalmiya, A., "Spectroscopic-Based DCN Prediction Using Functional Group Surrogate Informed Machine Learning Models," Thesis, University of Illinois at Chicago, 2023.
3) Johnson, K. J., R. E. Morris., S. L. Rose-Pehrsson., "Evaluating the predictive powers of spectroscopy and chromatography for fuel quality assessment," Energy and Fuels, Vol. 20, 2006, pp. 727–733

Dataset

Training

Name, description, or POSF (as applicable)	DCN
79 mixtures made using 23 neat hydrocarbons	15– 78.5
ARL-CN30	
ARL-CN35	34.70
ARL-CN40	36.70
ARL-CN45	41.90
ARL-CN50	49.70
ARL-CN55	55.09
F-24	59.50
ATJ – POSF11498	46.59
JP-10**	15.89
RP-2 – POSF5433**	18.85
RP-2 – POSF7688**	51.26
	51.29
* Used only with Dispersive NIR and ATR models ** Used only with Raman models	

Ignition Quality Tester used for DCN measurements

Testing

Name, description, or POSF (as applicable)	DCN
JetA1 – POSF10264	49.29
JetA2 – POSF10325	49.00
JetA3 – POSF10289 (JP5)	40.20
50/50 wt % ARL – CN35/CN55*	49.59
50/50 wt % ARL – CN35/CN45*	43.00
50/50 wt % ARL – CN30/CN50	45.09
50/50 wt % ARL – CN45/CN55	54.68
50/50 wt % ARL – CN35/CN40	39.79
50/50 wt % F-24/ATJ	34.59
30/70 wt % F-24/ATJ	29.60
70/30 wt % F-24/ATJ	39.50
20/80 wt % F-24/ATJ*	28.29
40/60 wt % F-24/ATJ	34.00
60/40 wt % F-24/ATJ	39.09
80/20 wt % F-24/ATJ	43.40
50/50 wt % JP10/ARL – CN55**	44.09
50/50 wt % JP10/F-24**	35.29
50/7.5/42.5 wt % JP10/ARL – CN55/F-24**	37.59
80/20 wt % CN35/CN55**	43.43
20/80 wt % CN35/CN55**	55.53
28/72 wt % CN30/CN45**	46.24
30/70 wt % CN40/CN50**	52.18
37.45/62.55 wt % CN40/CN55**	53.77
70/30 wt % CN30/CN35**	35.61
41.5/58.5 wt % CN30/CN35**	35.80
41.5/58.5 wt % CN40/CN45**	47.00
42/28.4/29.6 wt % CN30/CN55/F-24**	47.45
60/40 wt % CN30/CN40**	38.17
50/50 wt % CN30/F-24**	41.40
50/50 wt % CN45/F-24**	48.90
57/43 wt % CN30/CN40**	37.88
25/75 wt % CN55/F-24**	50.72
22/31/47 wt % CN40/CN50/F-24 **	50.28
65/35 wt % F-24/ATJ**	39.38
55/45 wt % F-24/ATJ**	36.73
50.5/49.5 wt % F-24/ATJ**	35.54

* Used only with Dispersive NIR and ATR models
** Used only with Raman models

Dataset comprised of:

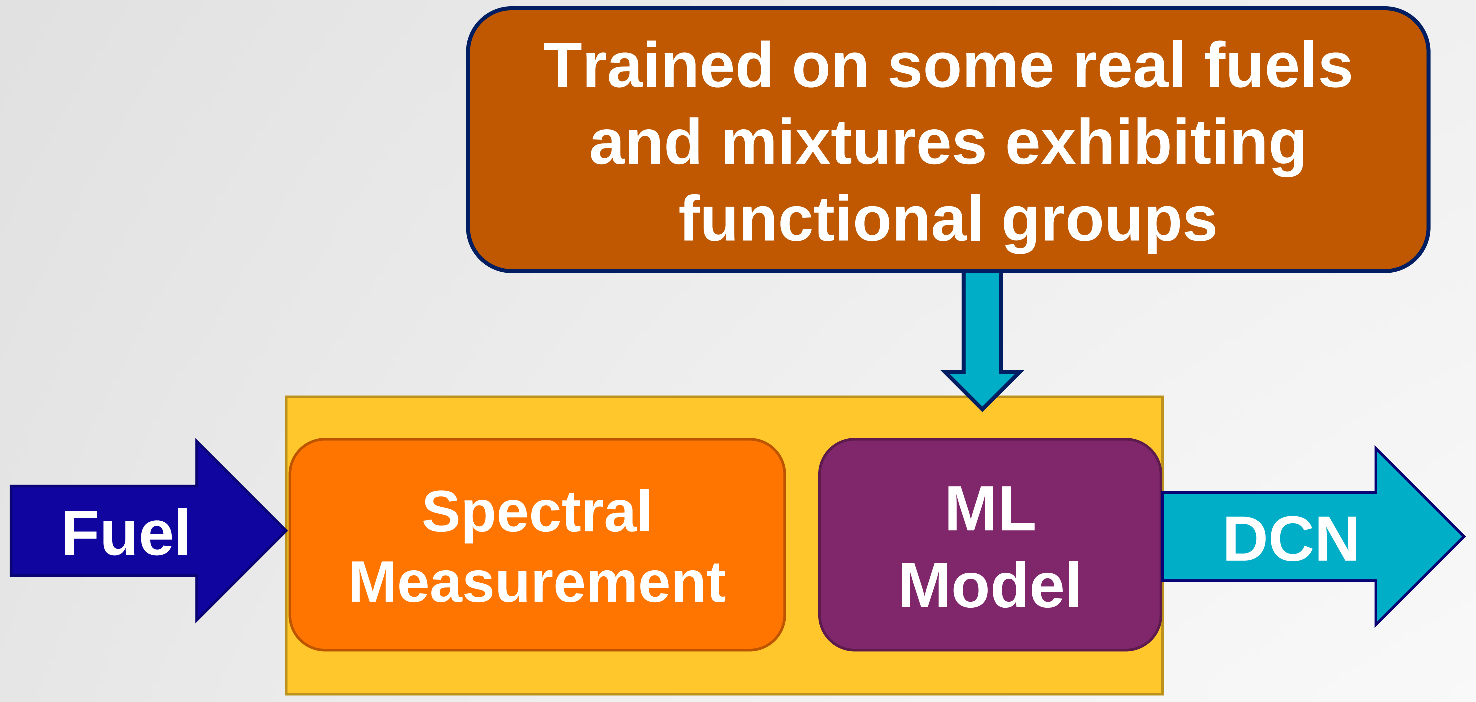
- Fuel surrogate mixtures
- Fuels
- Blends of fuels

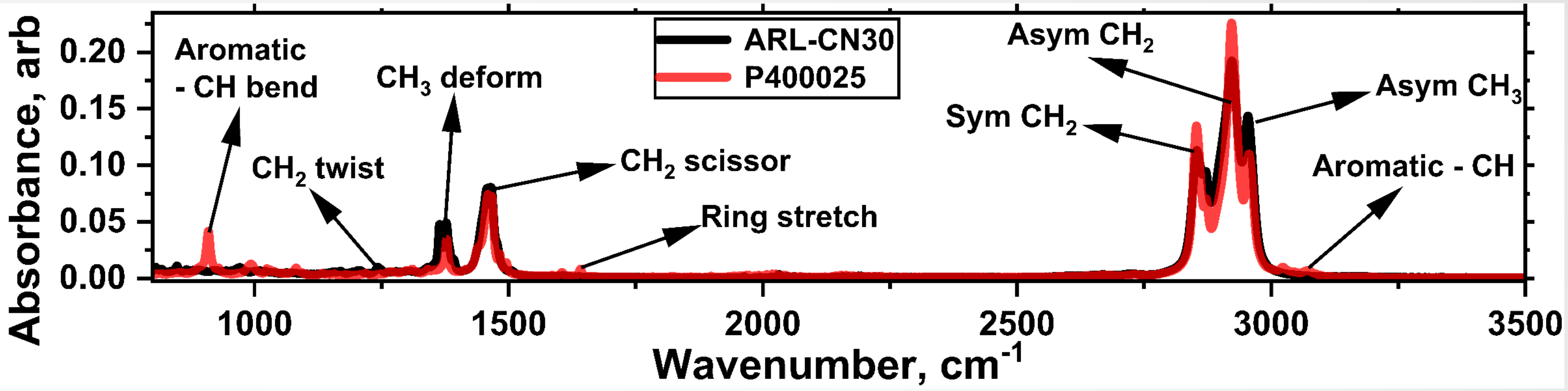
- Training ML models on all fuels is impractical
- Fuel surrogate mixtures were developed (mixtures of up to 4 neat hydrocarbons)

Selected neat HCs using GCxGC – TOFMS analysis

- HCs present in fuels
- Span the range of UNIFAC functional groups of jet fuels

Spectra to DCN Models





ARL – CN30: DCN = 34 **P400025: DCN = 53**

Spectroscopic Techniques	Spectral Range* (cm^{-1})	R^2 Score	MPE (%)	% of samples within ±10% error
Dispersive NIR	10500 – 6056 (952 – 1651 nm)	0.86	5	97
FT-ATR [1]	3200 – 800	0.89	4.58	95
Raman [2]	1800 – 500 (Raman shift from 785 nm laser)	0.89	4.69	93.33

* Spectral range required for ML model to perform predictions

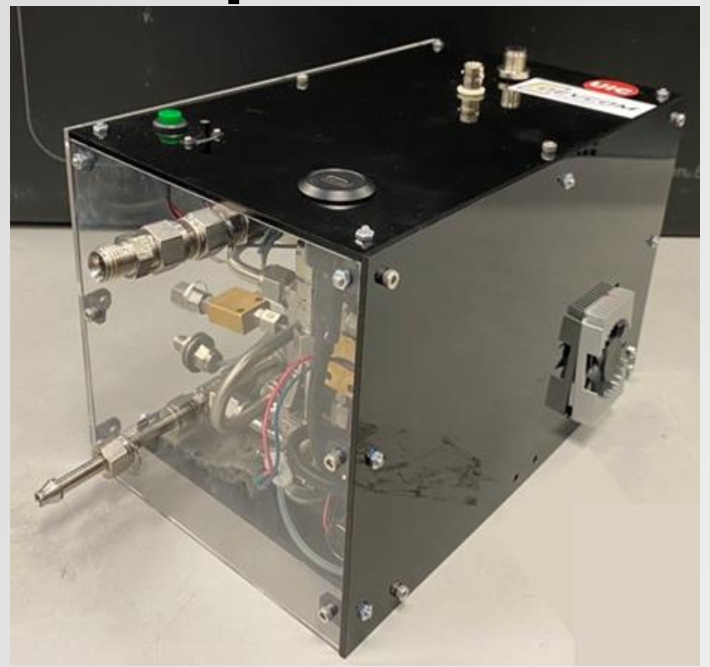
Things to keep in mind:

- Resilience to outliers

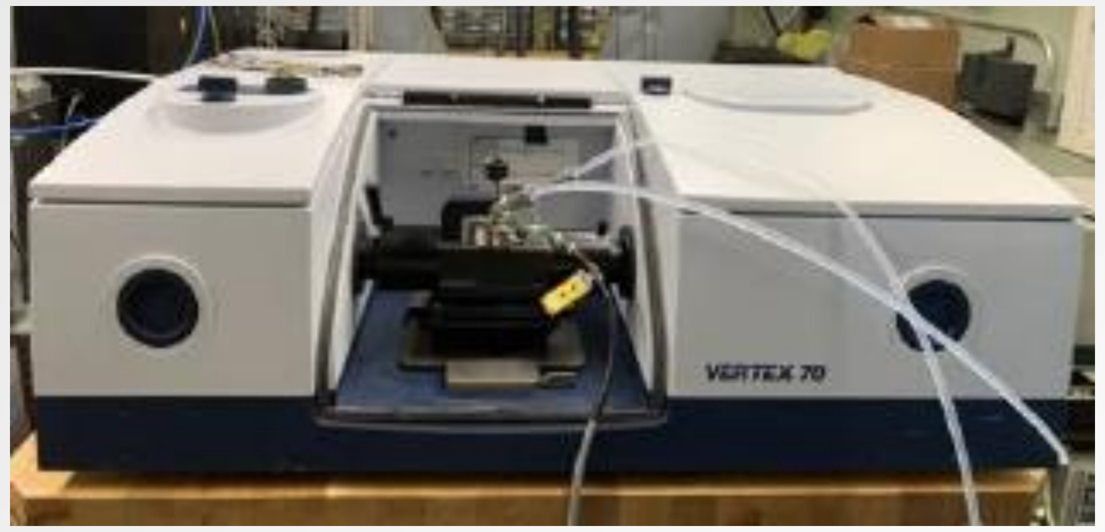
1) Dalmiya, A., M. Sheyyab., E. K. Mayhew., K. Brezinsky., P. T. Lynch., Comparison of Infrared Spectroscopic Methods in Predicting DCN of Jet Fuels and Their Blends Using Chemometric Tools, in: Vol. 4 Control. Diagnostics, Instrum., American Society of Mechanical Engineers, 2023: pp. 1–9.
2) Dhananjay Ambre, Manaf Sheyyab, Patrick Lynch, Eric K. Mayhew, Kenneth Brezinsky, A Raman spectroscopy based chemometric approach to predict the derived cetane number of hydrocarbon jet fuels and their mixtures, Talanta, Volume 271, 2024, 125635

Spectroscopic Fuel Sensor Prototypes

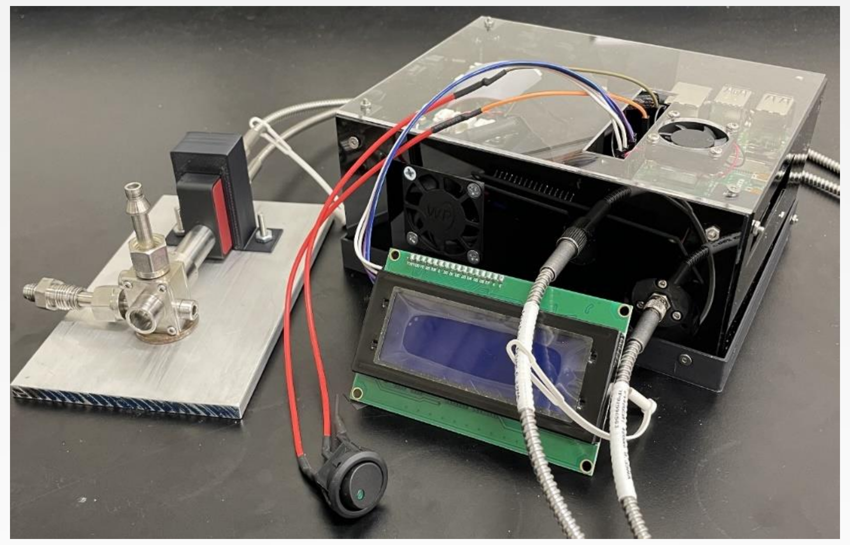
Dispersive NIR



FT-ATR



Raman



	Dispersive NIR	FT-ATR	Raman
Volume (cm^3)	6223	147844	2490
Weight (kg)	3	70	1
Peak Power Load (W)	9	180	8
Time Response (s)	10	3	18
Spectral Range*	900-1700 nm	4000-400 cm^{-1}	1800-500 cm^{-1} (Raman shift from 785 nm laser)
Spectral Resolution	10 nm	2 cm^{-1}	7 cm^{-1}

* Spectral range the spectrometer is capable of measuring

[1]

Criteria	Proposed Metric(s)
Accuracy	
• Long-term accuracy (e.g., DCN)	Model-based analysis (% of samples within 10% of DCN) at steady state
• Startup accuracy (e.g., DCN)	Prototype or possibly model analysis (% of samples within 10% of DCN) within 1 minute
• Model vs. sensor accuracy	% accuracy of a known test set on prototype deployed sensors
• Accuracy derating with temperature, vibration	To be determined, typically rated as %/°C, etc.
• Likelihood of measurements of other properties	Model-based analysis of other properties. Number of chemical functional groups that can be accurately assigned to a specified accuracy.
• Outlier Resistance /Resilience to fuels outside of the training set	Model-based analysis on a restricted challenge set. Possible accuracy bands on ranges very different from jet fuels.
Physical Criteria	
• Pressure drop, No cavitation	Curves of pressure drop vs. flow rate, pressure drop at one condition
• Response time	Response time, time until recalibration, duty cycle
• Power consumption	Steady-state and peak power consumption
• Weight	Total weight
• Volume	Total volume, largest dimension
Robustness	
• Chemical compatibility	Time to failure for wetted parts with specified fuel set
• Vibrational	Survivability → Exposure to high g and frequencies, modified MIL-SPEC evaluation.
• Temperature	Survivability → Exposure to -46 to 71°C, modified MIL-SPEC evaluation
Other engineering considerations	
• Required orientation	Maximum tilt (°)
• Cost	Cost, number of components, etc.

1) Abhinav Abraham, Dev Patel, Anandvinod Dalmiya, Ashish Sutar, Haruna Okada, Dhananjay Ambre, Manaf Sheyyab, Kenneth Brezinsky, Scott Sanders and Patrick T. Lynch. "Characteristics of Onboard Sensors for Fuel Ignition Performance," AIAA 2024-1244. *AIAA SCITECH 2024 Forum*. January 2024.

Demonstration Setup

Objective

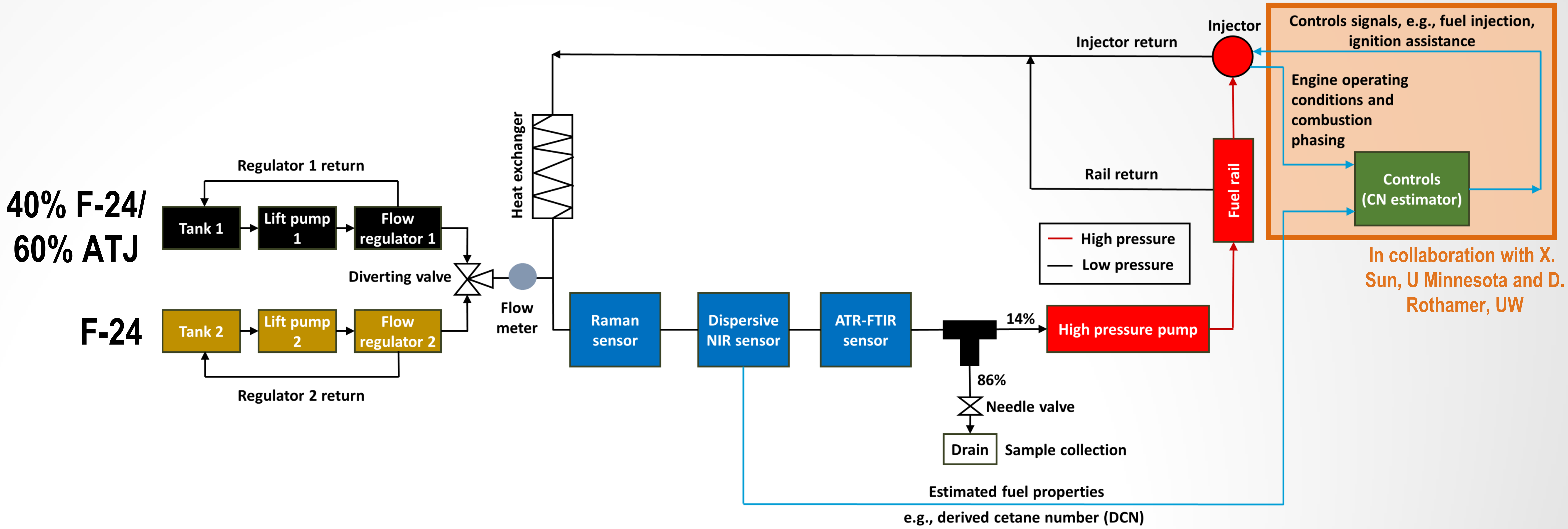
- Demonstrate the capability of the fuel sensors in providing accurate DCN predictions real time and inline with an engine for combustion phasing control

Approaches

- Integrate the fuel sensors with an engine test cell at UW and its engine controls (CN estimator) developed by UMN
- Validate the accuracy of the DCN predictions provided by the sensors during fuel switching using an IQT

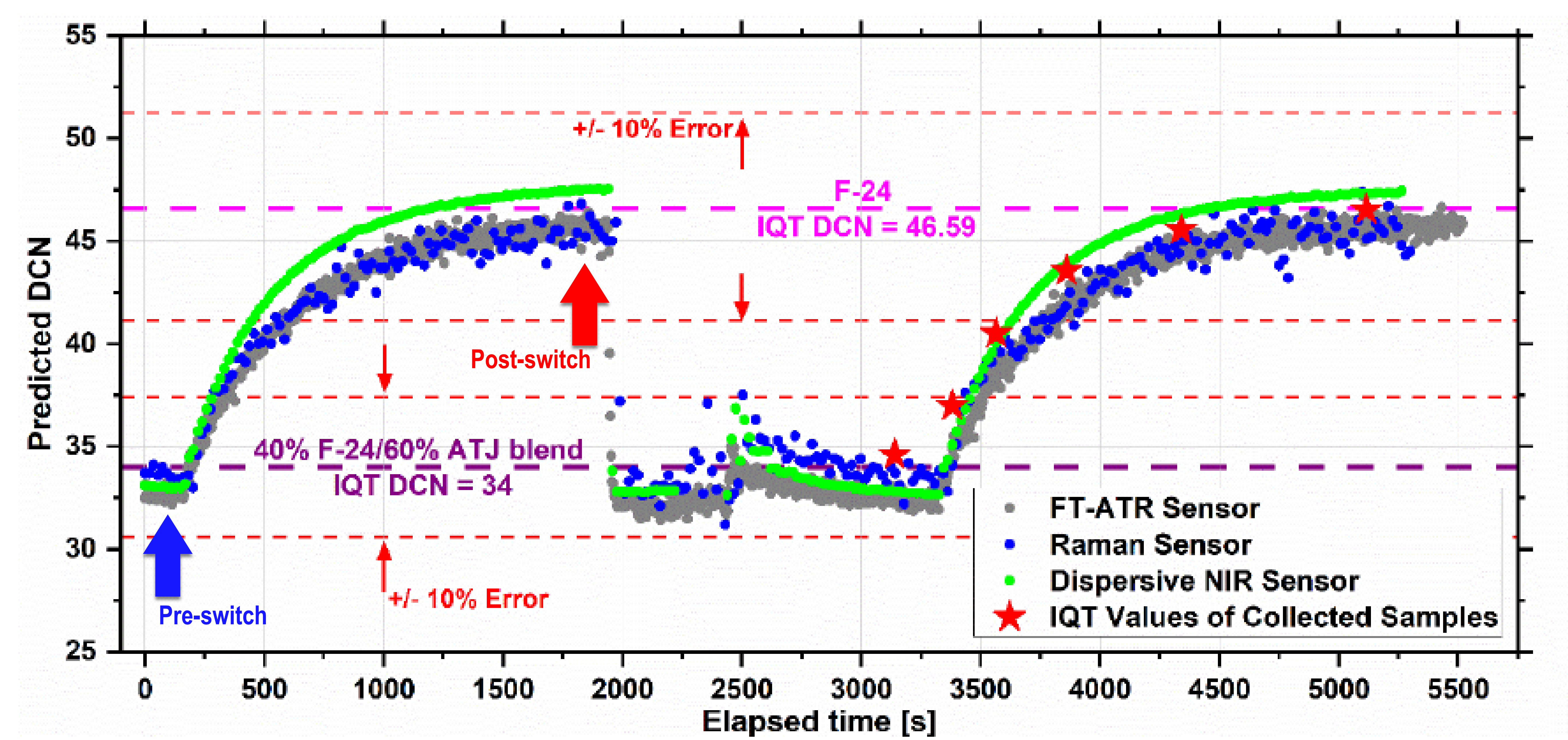
Property	Units	F24	40% F-24/ 60% ATJ	ATJ
DCN*	-	46.59	34	17.42
LHV	MJ/kg	43.1	43.7	43.9
ρ @ 288 [K]	kg/m^3	803.7	777	761
ν @ 313 [K]	mm^2/s	1.377	1.446	1.53
Aromatics	% vol.	15.4	6.3	<0.01
Olefins	% vol.	1.2	1.4	0
Saturates	% vol.	83.4	92.4	99.62
T10**	°C	176.5	177	178.9
T50**	°C	207.7	189.8	183.3
T90**	°C	250.6	241	224.4

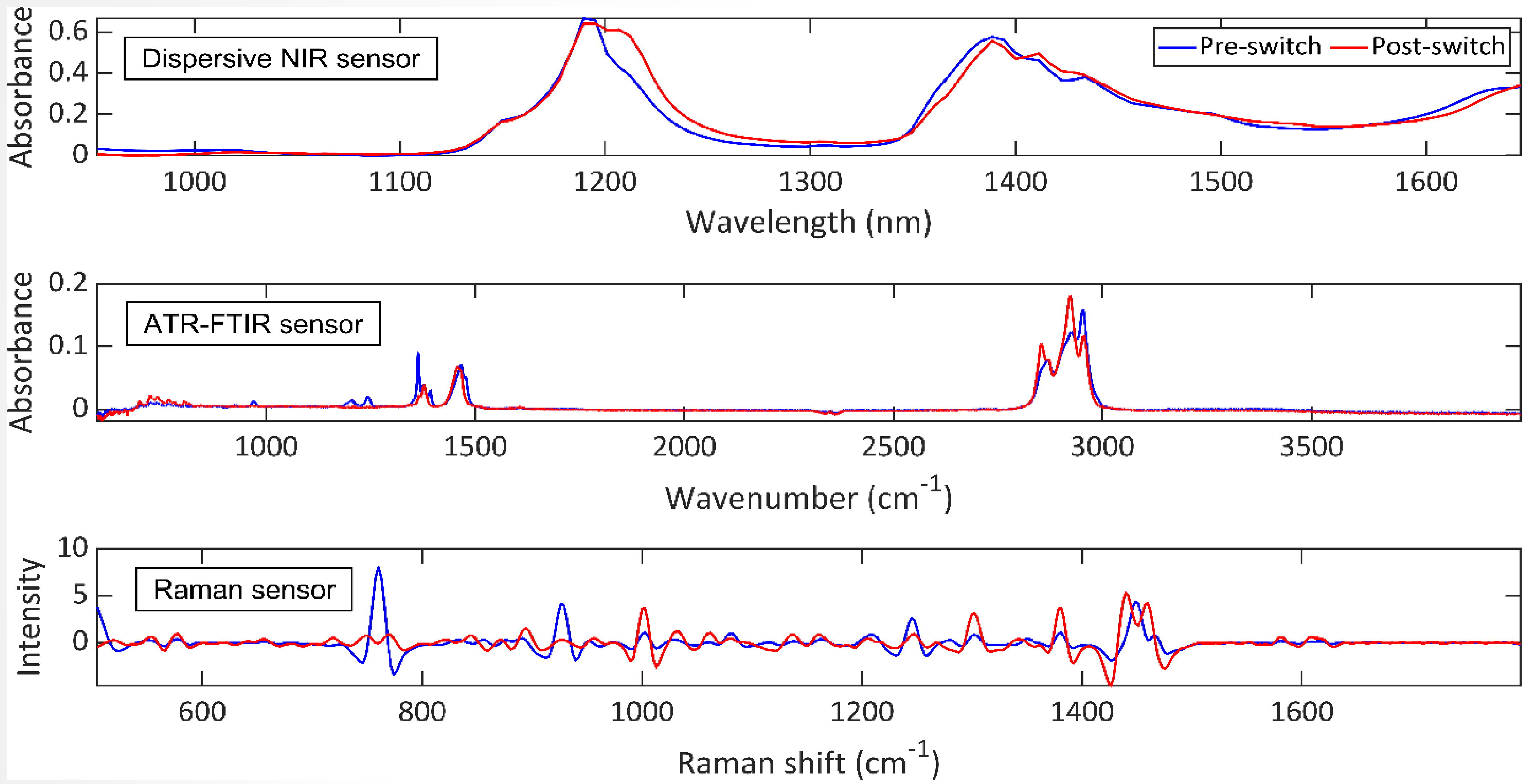
*ASTM D6890
** ASTM D86

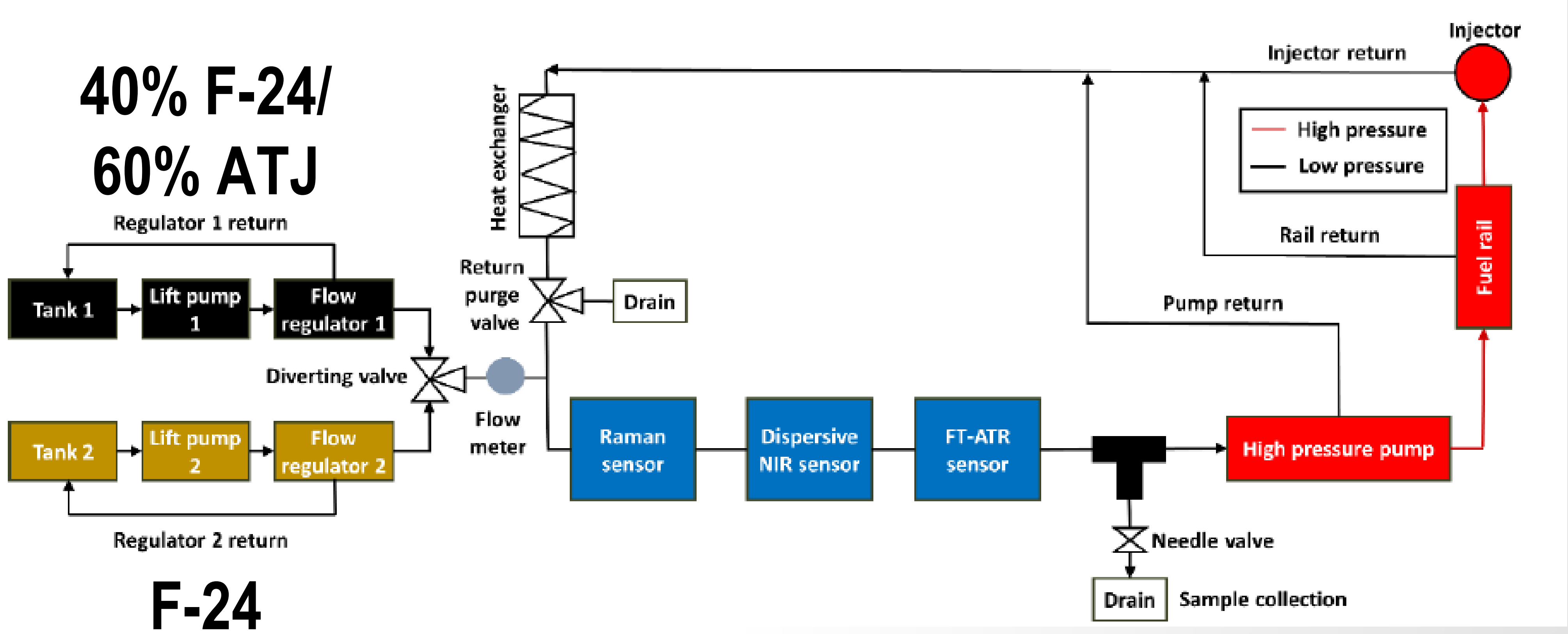


In collaboration with X. Sun, U Minnesota and D. Rothamer, UW

Experimental Results







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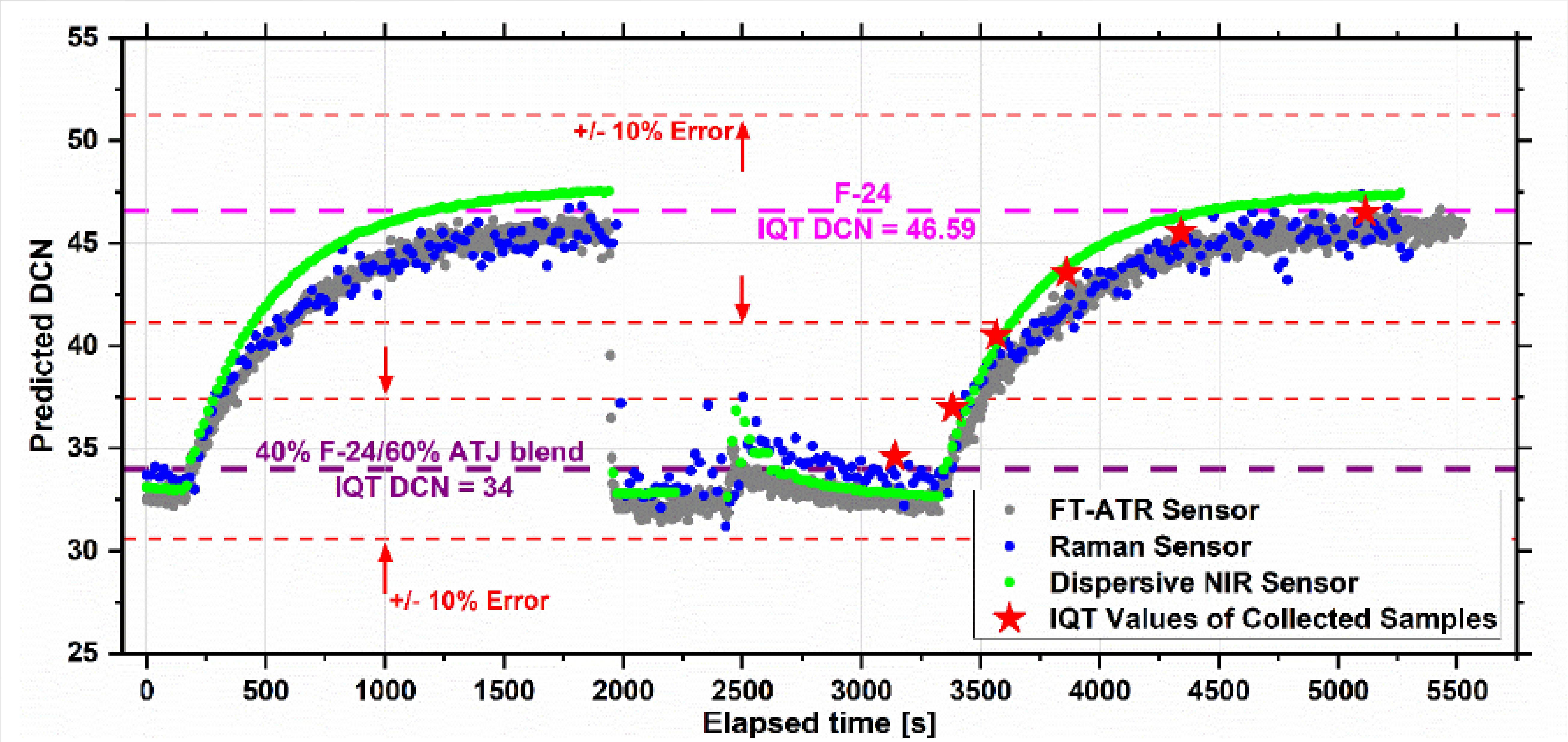


Sensor	Percent error [%]						Average absolute percent error [%]
	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	
Dispersive NIR	-5.21	-1.90	0.38	1.40	2.10	1.73	2.12
Raman	-4.11	0.50	-1.32	-4.40	-1.63	-2.05	2.34
FT-ATR	-6.12	-2.97	-4.04	-2.74	-1.80	-1.92	3.27

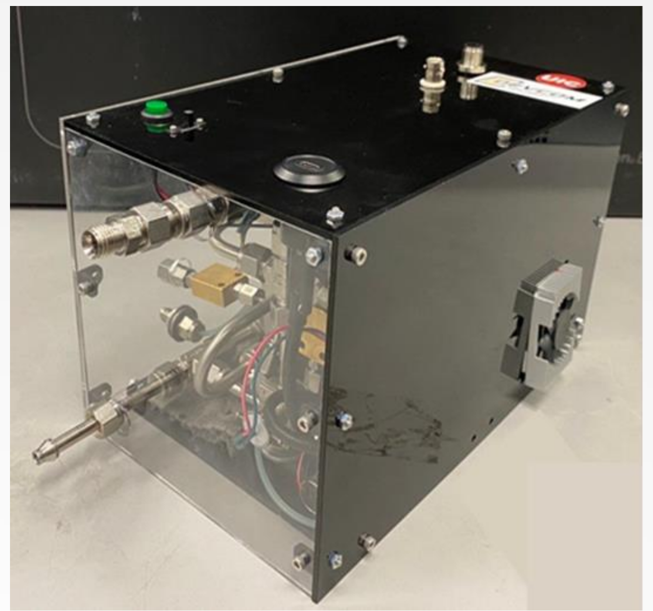
Key takeaways:

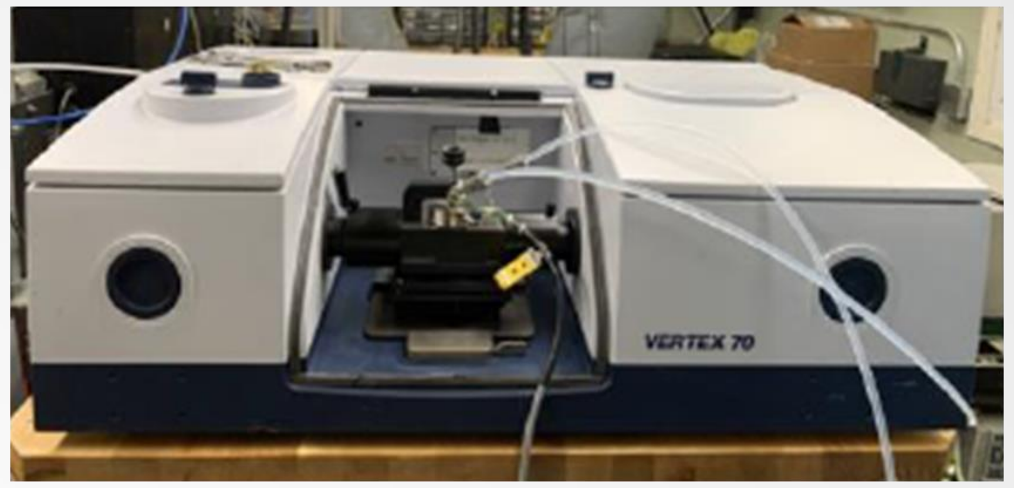
- All three sensors performed accurate real time predictions within the desired +/- 10% error inline with an engine
- Dispersive NIR fuel sensor had the lowest average percent error when compared to DCN values obtained from IQT measurements

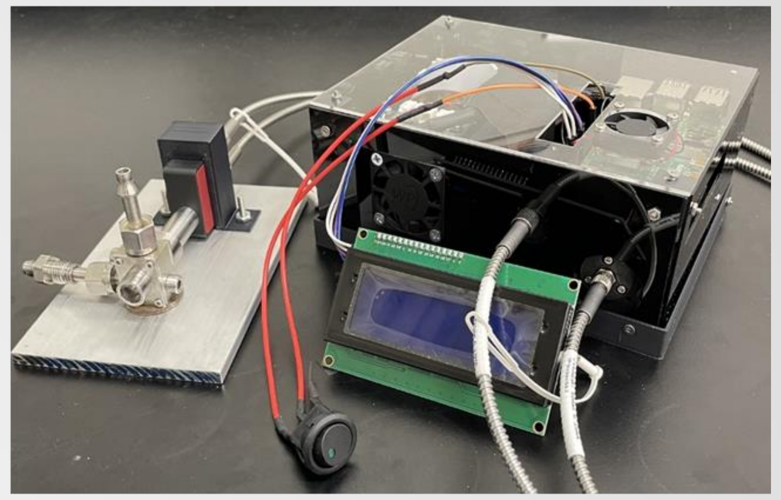
Next Steps

Robustness of Sensors:

- Current sensor lineup comprised of parts and components not tested according to MIL-SPEC-STD
- Reduce susceptibility to vibrational effects (misalignments)
- Rigidity to handle deployment conditions and environments





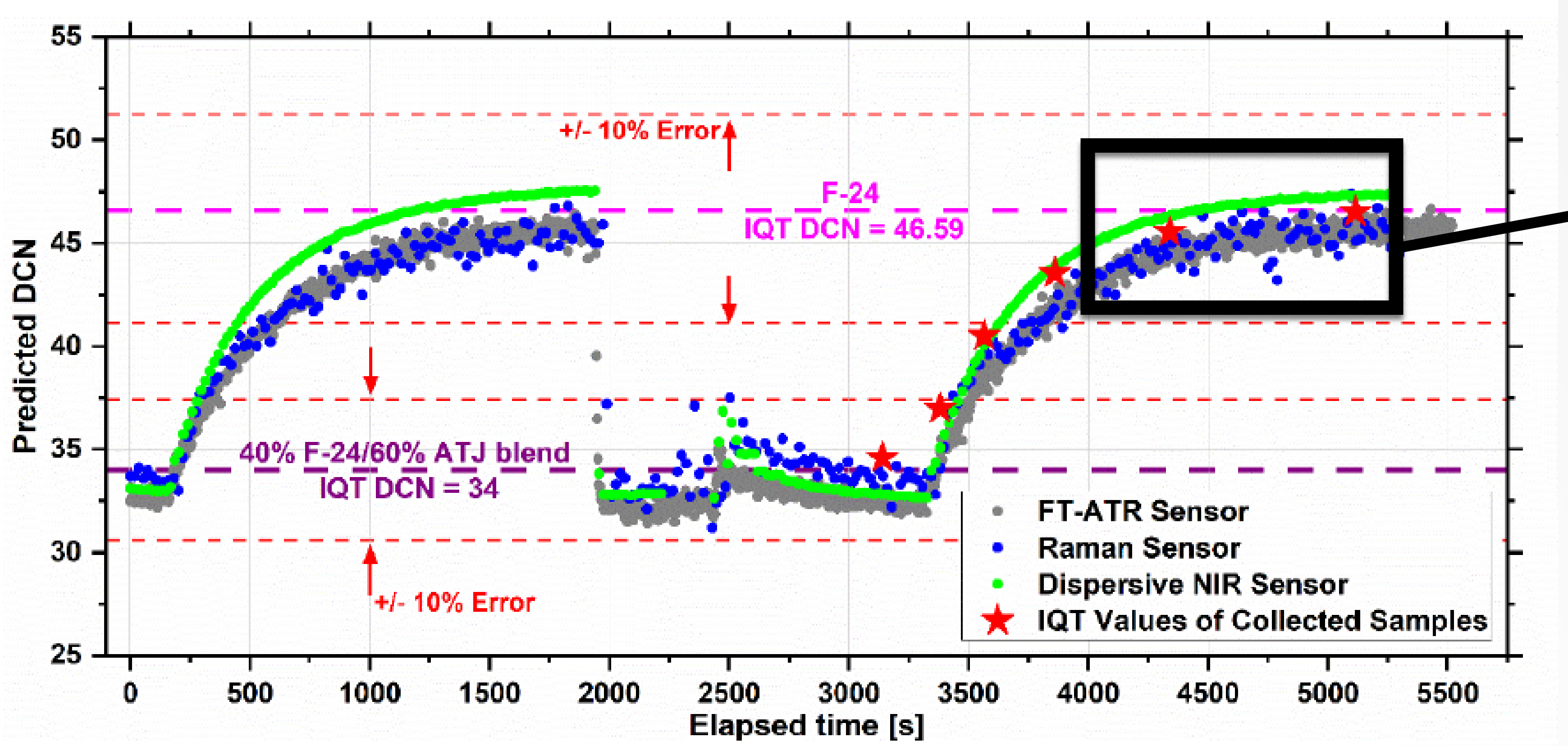


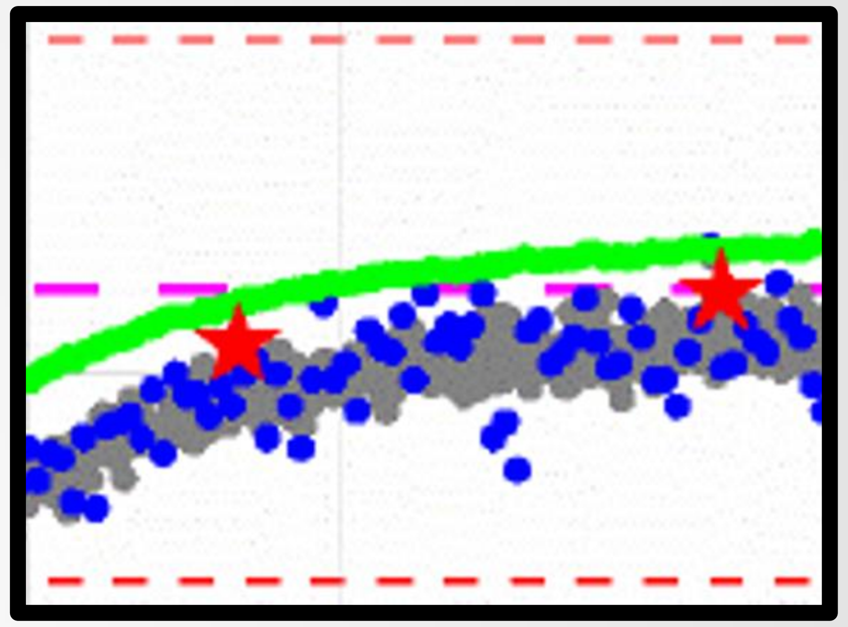
Improve predictive capabilities:

- Improved prediction accuracy
- Handle shot-to-shot prediction variations (prediction smoothing/averaging?)
- Evaluate models with outliers

Further integration with engine controls:

- Increase impact/use of sensor predictions for engine





Work in Progress and Future Work

Further miniaturize and improve fuel sensors

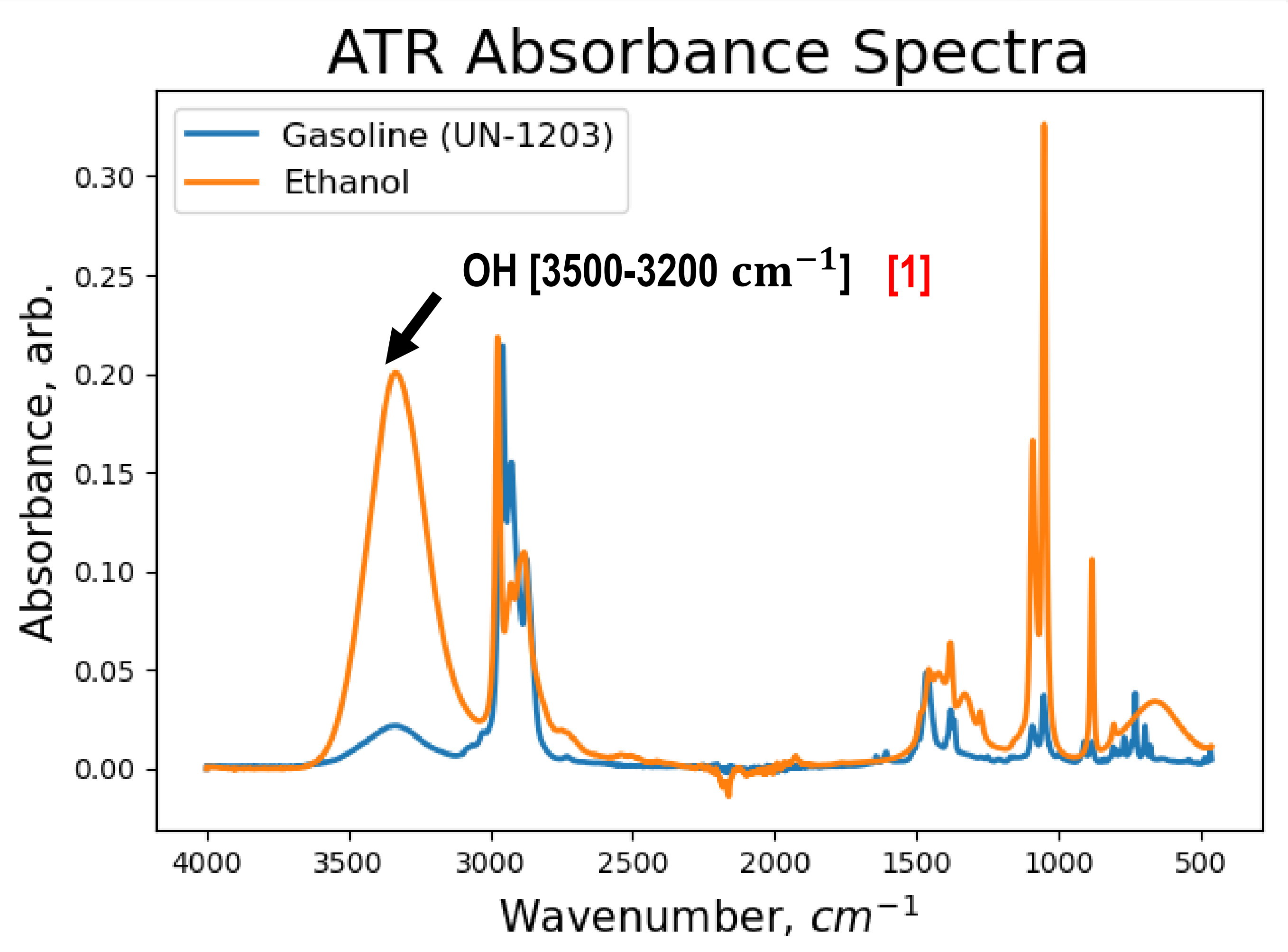
- Reducing size, weight and power (SWAP) requirements of the sensor while maintaining prediction accuracy

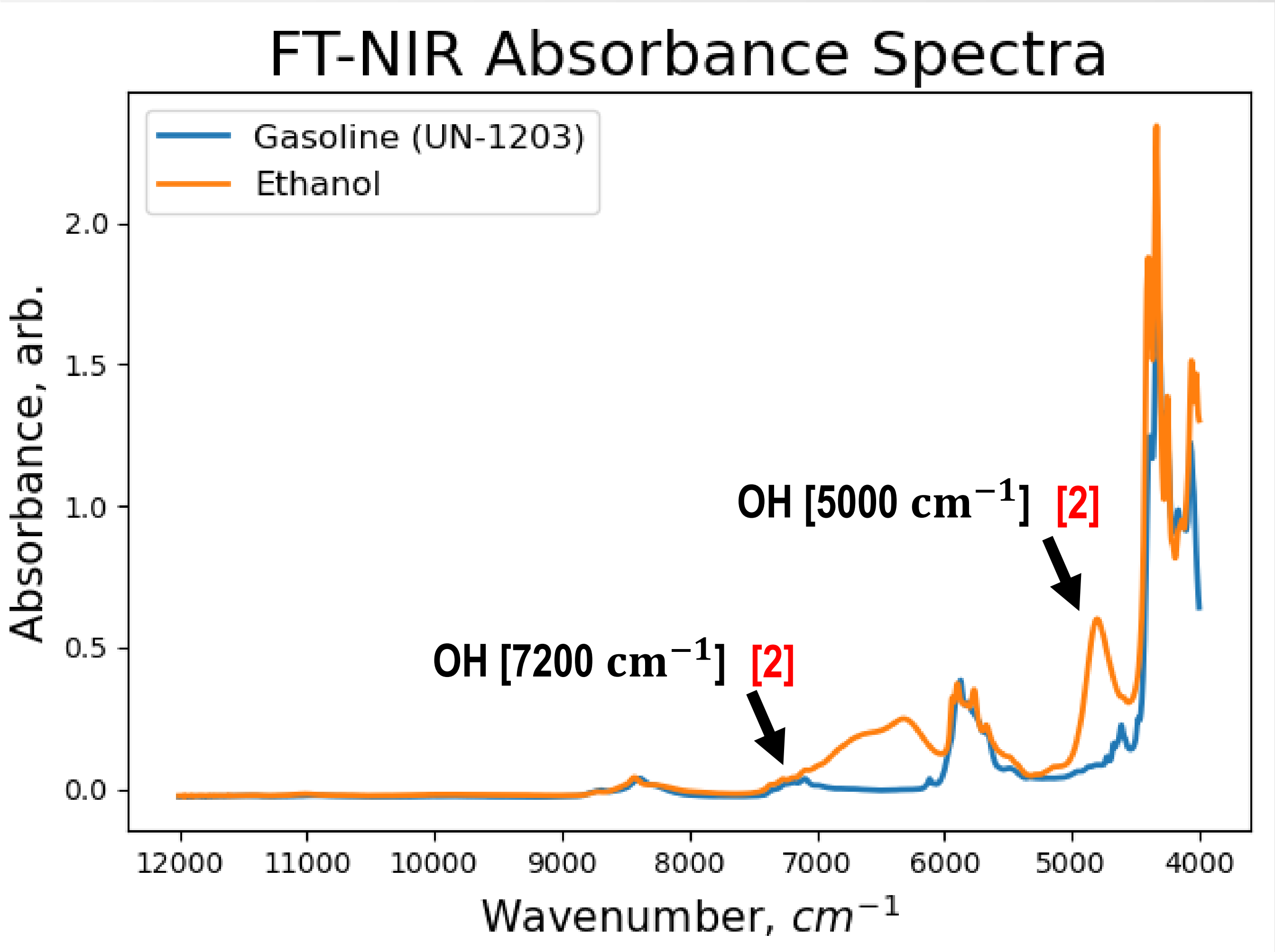
Expanding capabilities for additional fuels

- Current dataset is comprised of hydrocarbons

[CH_3, CH_2, CH, C, CH_2=CH, CH=C, ACH, AC, $ACCH_3$, ACCH ACCH, CH≡C]

- Working on expanding to incorporate OH





Expanding capabilities for additional fuel properties

- Investigating feasibility to predict density, latent heat of vaporization and enthalpy demand of fuels

1) Nakanishi, Kōji. *Infrared Absorption Spectroscopy, Practical*. Holden-Day, 1962, 1962.
2) Beć KB, Wójcik MJ, Nakajima T. Quantum Chemical Calculations of Basic Molecules: Alcohols and Carboxylic Acids. NIR news. 2016;27(8):15-21. doi:10.1255/nirn.1650

Work in Progress and Future Work

Modify previously proposed criteria for UAS applications to better fit needs and requirements for GV applications

- Do sensors deployed on GVs need to have the same accuracy requirements as UAS applications?
- Can the sensors have larger SWAP requirements?

[1]

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Dr. Mike Kweon is the program manager of VICTOR ERP. Dr. Jacob Temme is the deputy program manager.