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DOE Bioenergy Technologies Office (BETO) 2019 Project Peer Review

ADO Session Presentation

Feedstock to Function Tool: Improving biobased product and fuel development through
adaptive technoeconomic and performance modeling

March 7, 2019

Technology Session Area Review

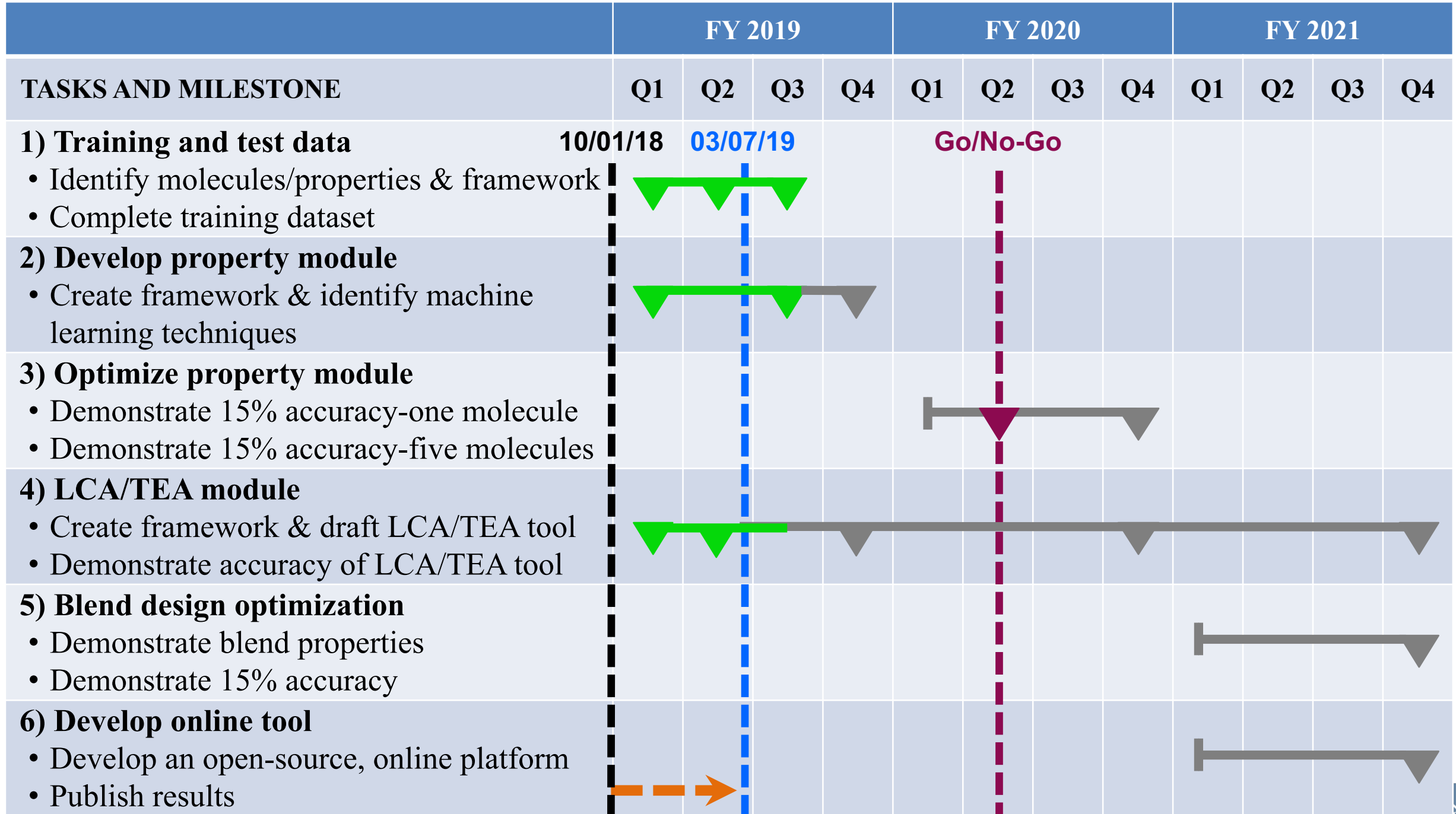
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Goal Statement

Increase domestic energy security and reducing U.S. reliance on foreign oil by developing a flexible, open-source tool that:

- Predicts properties of high-potential molecules (fuels, fuel co-products, and other bioproducts) derived from biomass using the power of machine learning
- Evaluates the cost, benefits, and risk of promising biobased molecules or biofuels to enable faster, less expensive bioprocess optimization, certification, and scale-up
- Aids industry with making progress towards the \$3 per gallon goal



Project Budget Table

	Original Project Cost (Estimated)		Project Spending and Balance		Final Project Costs
Budget Periods	DOE Funding	Project Team Funding Allocation	Spending to Date	Remaining Balance	Funding needed to complete project
FY 2019	\$350K <i>(\$325K received)</i>	LBNL (78%) OSU (22%)	\$14K (spent) \$52K (encumb.)	\$284K <i>(\$259K of received)</i>	
Task 1: Training and test datasets		LBNL (100%)			
Task 2: F2F property module		LBNL (53%) OSU (46%)			
Task 4: F2F LCA/TEA module		LBNL (100%)			

Project Budget Table (continued)

Budget Periods	Original Project Cost (Estimated)		Project Spending and Balance		Final Project Costs
	DOE Funding	Project Team Funding Allocation	Spending to Date	Remaining Balance	Funding needed to complete project
FY 2020	\$350K	LBNL (69%) OSU (31%)			
Task 3: Optimize property module		LBNL (64%) OSU (36%)			
Task 4: F2F LCA/TEA module		LBNL (100%)			
FY 2021	\$350K	LBNL (81%) OSU (19%)			
Task 4: F2F LCA/TEA module		LBNL (100%)			
Task 5: Blending Design		LBNL (54%) OSU (46%)			
Task 6: F2F online tool		LBNL (89%) OSU (11%)			

Quad Chart Overview

Timeline

- Project start date 10/1/2018
- Project end date 9/30/2021
- Percent complete ~14%

Barriers addressed:

- ADO-C. Codes, Standards, and Approval for Use
- Ct-J. Identification and Evaluation of Potential Bioproducts
- Ct-N. Multiscale Computational Framework toward Accelerating Technology Development

	FY 19 Costs	Planned FY 20 Costs	Planned FY 21 Costs	Total Planned Funding (FY 19-Project End Date)
DOE Funded	\$350K	\$350K	\$350K	\$1050K
Project Cost Share*	LBNL (78%) OSU (22%)	LBNL (69%) OSU (31%)	LBNL (81%) OSU (19%)	LBNL (76%) OSU (24%)

Partners:

Oregon State University (OSU)

Other Collaborations:

- Coordinating with NREL to obtain relevant data from Co-Optima database
- Collaborate with and support existing efforts for a future jet program: Sandia, NREL, PNNL, Dayton University, Georgia Tech

1 - Project Overview

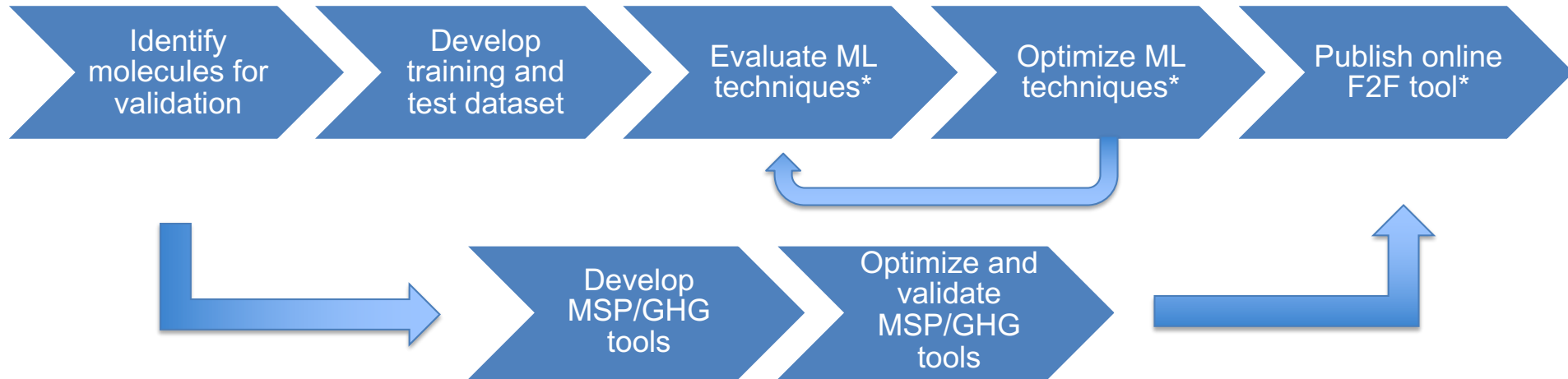
Advancements of bio-derived alternative jet fuels are limited by significant technical, social, and regulatory barriers

Standard property testing biofuel and biofuel blends is expensive, requires high fuel-volume for certification, and is conducted years after initial bench-scale experiments

High-Level Objectives:

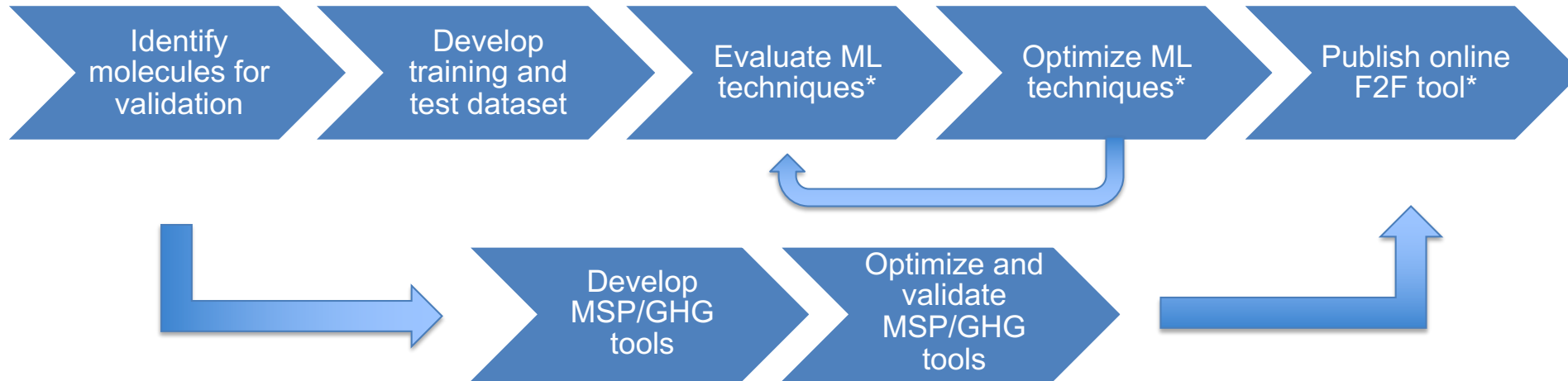
- Develop and optimize machine learning (ML) techniques to predict properties of selected neat potential alternative jet molecules and blends
- Develop lightweight minimum selling price (MSP) and greenhouse gas (GHG) emissions estimation tool
- Develop and demonstrate an online tool that uses ML to predict desired properties and evaluate the cost, benefits, and risk of promising bio-based molecules or biofuels

2 – Technical Approach



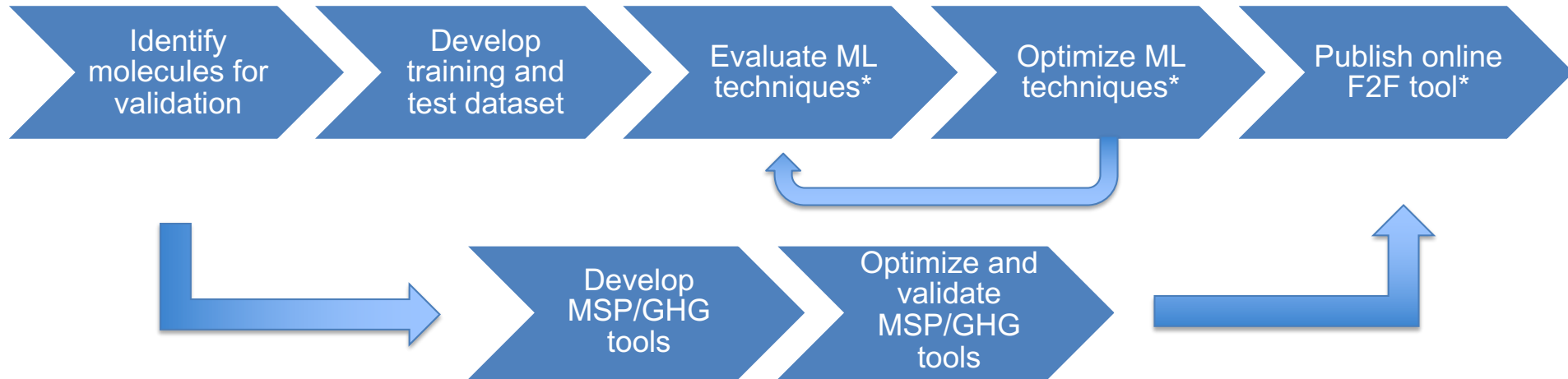
- **Develop dataset for machine learning (ML) based property prediction [LBNL]**
 - Leverage 400+ molecules and blends from Co-Optima database, NIST, and literature
 - Include required properties from ASTM D7566 certified alternative jet fuels and validate properties with industry
- **Develop and optimize framework for property prediction [LBNL & OSU]**
 - Automated machine learning tools in Python (e.g. TPOT, `scikit.learn`) to evaluate and rank supervised ML techniques for property prediction of neat molecules
 - Optimize algorithm(s) to improve predictive performance and inform Go/No-Go decision

2 – Technical Approach (continued)



- **Develop minimum selling price (MSP) and greenhouse gas emissions (GHG) estimation tools [LBNL]**
 - Develop a lightweight technoeconomic (TEA) and life-cycle assessment (LCA) model to estimate minimum selling price and life-cycle greenhouse gas emissions
 - Include potential tradeoffs between production-phase impacts and use-phase impacts
- **Publish online F2F webtool [LBNL & OSU]**
 - Output predicted (using identified ML techniques) and measured neat and blend properties, cost analysis, and GHG emissions with sensitivity analysis

2 – Technical Approach (continued)



- **Metrics of Success**

- Demonstrate predicted properties (neat and blends) are within 15% of published values
- Publish online F2F tool that predicts properties for potential alternative jet fuel molecules

- **Challenges**

- Identifying and validating algorithm(s) to ensure accuracy, reduce computational resource demand, and reduce risk to schedule and scope
- Collecting an abundance of reliable and accurate property data to accurately train tool
- Validating lightweight TEA methods can predict mass/energy balances and costs

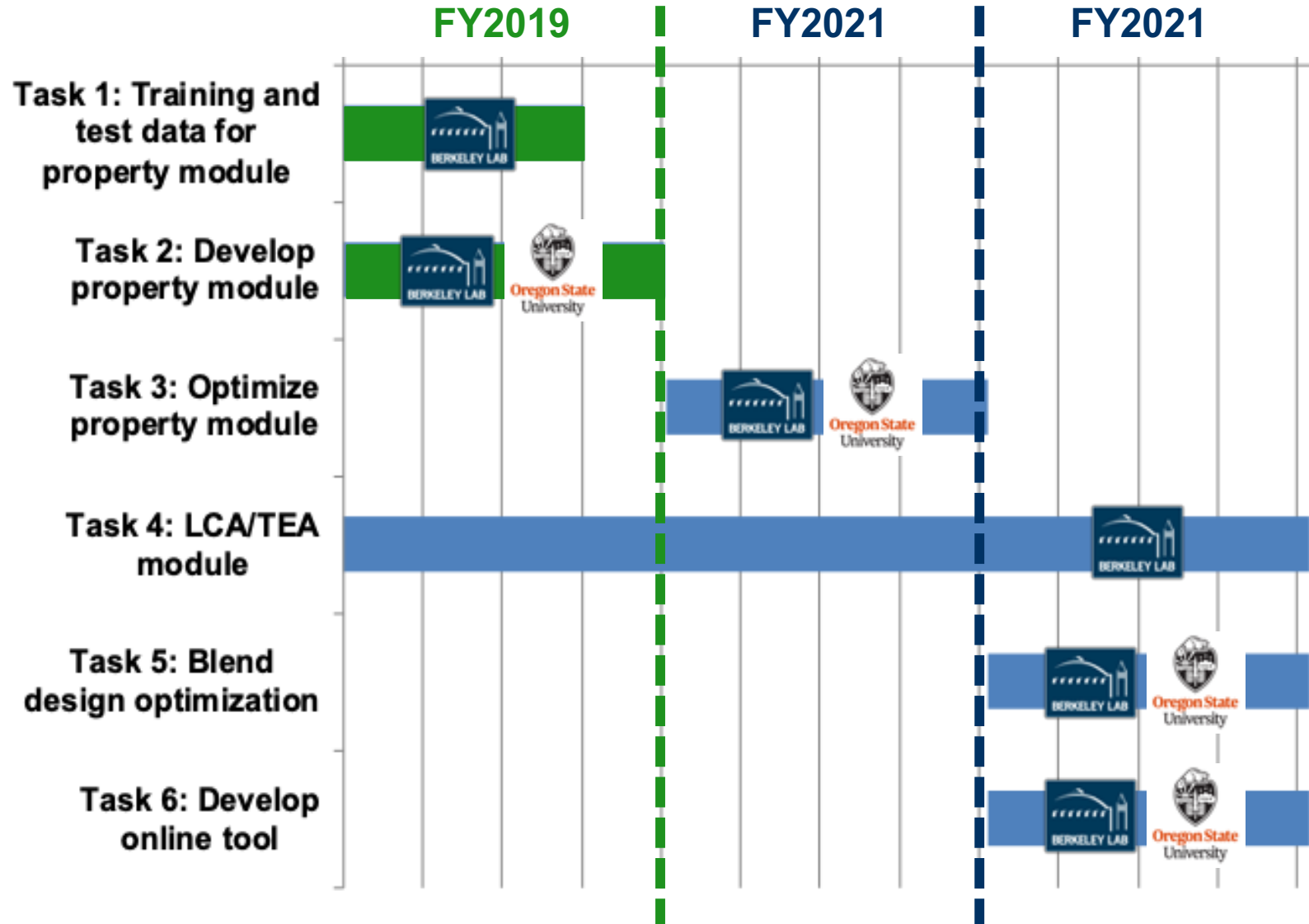
2 – Management Approach (Management)

OSU Milestones/Deliverables

- Weekly project updates
- Quarterly progress reports
- Software/source code development in support of the tasks

Other Potential Partnerships

- NREL - Co-Optima Program
- Existing efforts for jet program: Sandia, NREL, PNNL, Dayton University, Georgia Tech



3 – Technical Progress

Key Accomplishments

- On-schedule for quarterly milestones
 - Database has 400+ different molecules and blends
 - Initiated evaluation of ML techniques for property prediction
 - Confirming with industry identified high-priority molecules and properties for database
- Ahead of schedule on future milestones
 - Predicted minimum selling price (MSP) and GHG emissions from limonene
 - Predicted cetane number of jet fuels
 - Created framework for online tool

TASKS AND MILESTONE	FY 2019				FY 2020			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
1) Training and test data <ul style="list-style-type: none"> • Identify molecules/properties & framework • Complete training dataset 	Completed							
2) Develop property module <ul style="list-style-type: none"> • Create framework & identify machine learning techniques 								
3) Optimize property module <ul style="list-style-type: none"> • Demonstrate 15% accuracy-one molecule • Demonstrate 15% accuracy-five molecules 								
4) LCA/TEA module <ul style="list-style-type: none"> • Create framework & draft LCA/TEA tool • Demonstrate accuracy of LCA/TEA tool 								
					Go/No-Go			

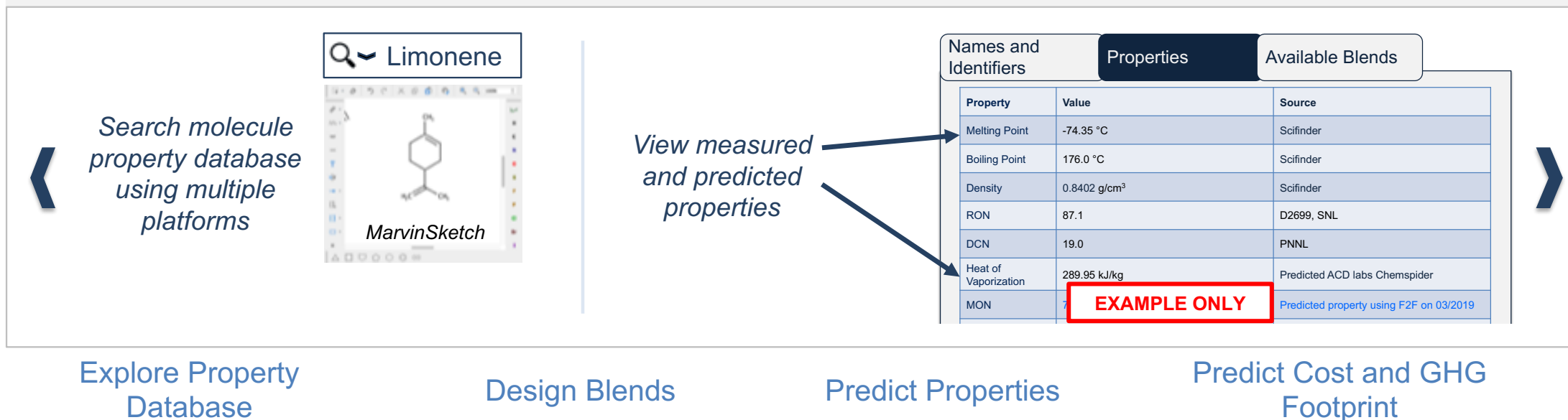
3 – Technical Progress: Framework for F2F website



Home About Tools Data Sources Documentation References

Feedstock to Function Tool

The 'Feedstock to Function' tool harnesses the power of machine learning to predict properties of high-potential molecules derived from biomass and evaluates the cost, benefits, and risk of promising biobased molecules or biofuels to enable faster, less expensive bioprocess optimization and scale-up.



3 – Technical Progress: Framework for modules

The screenshot shows the 'FEEDSTOCK TO FUNCTION' web application. The navigation bar includes Home, About, Tools, Data Sources, Documentation, and References. The main menu has four options: Explore Property Database, Design Blends, Predict Properties, and Predict Cost and GHG Footprint. The 'Predict Properties' section is active, showing a 'Select Molecule by Structure' dropdown set to 'Predict Properties' and a chemical structure of Limonene. Below this is a 'Select Properties' section with checkboxes for Melting Point, Boiling Point, Density, DCN, Heat of Vaporization, Smoke Point, Flash Point, Volatility, Autoignition Temperature, Specific Energy, and Energy Density. The 'Predicted Blend Properties' table is shown below.

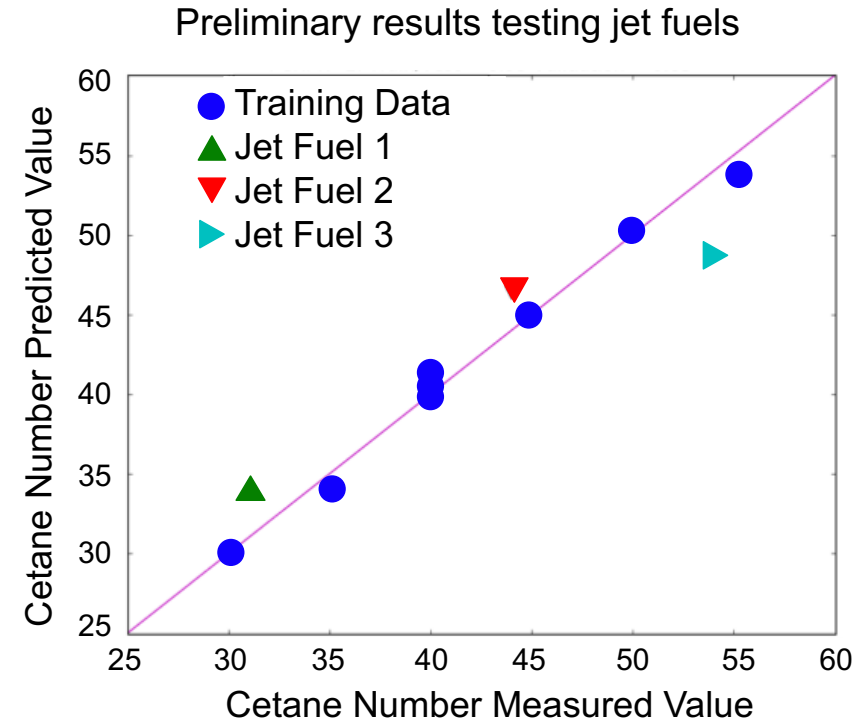
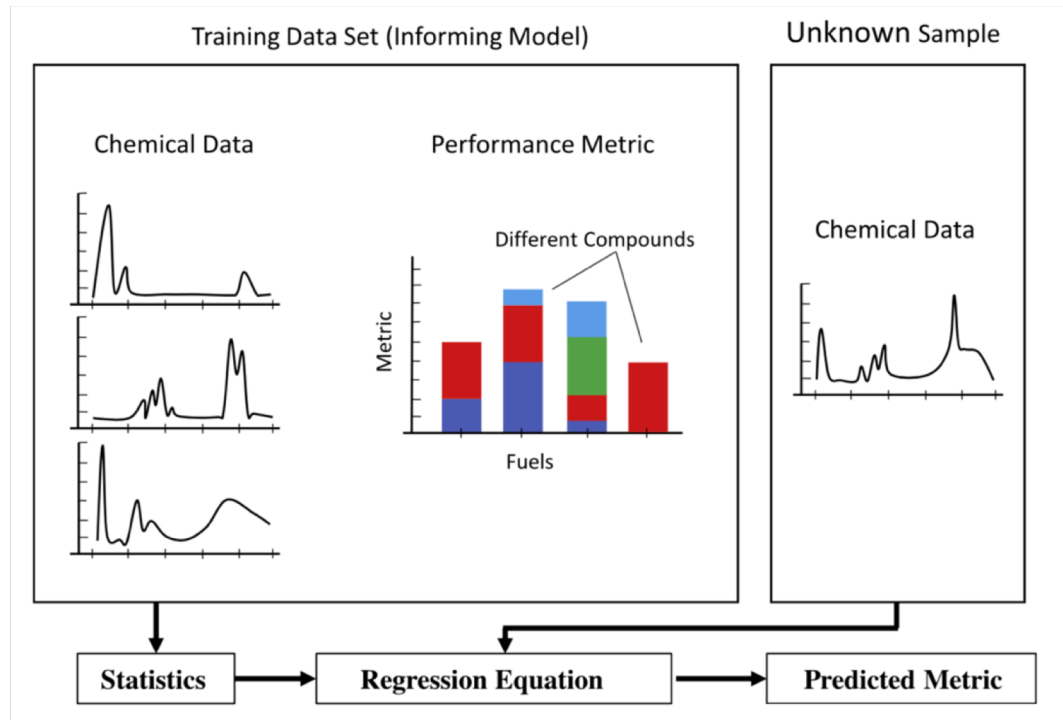
Property	Predicted Value	Accuracy	Algorithm
DCN	41.0	100%	1. Predicted by CD labs Chemspider
Heat of Vaporization	260.00 kJ/kg	100%	1. Predicted by CD labs Chemspider

Predict Properties of New Molecules

The screenshot shows the 'FEEDSTOCK TO FUNCTION' web application. The navigation bar is the same as the previous screenshot. The main menu has four options: Explore Property Database, Design Blends, Predict Properties, and Predict Cost and GHG Footprint. The 'Predict Cost and GHG Footprint' section is active, showing a 'Select Output Molecule' dropdown set to 'Limonene'. Below this are buttons for 'Run GHG Model', 'Run Water Consumption Model', 'Run Water Withdrawal Model', and 'Run Cost Model'. There are also buttons for 'Use Default Values' and 'Use SuperPro Values'. The 'Common Parameters' section includes: GWP time horizon [years] = 100, biorefinery electricity source [region] = US, feedstock = Sorghum, ionic liquid = [Ch][Lys]. The 'Recovery and Separation Process' section includes: electricity [kWh per kg of fuel] = 0.13, biorefinery cooling water [liters per kg fuel] = 152l, biorefinery steam low heat [kg per kg fuel] = 9.59, biorefinery steam high heat [kg per kg fuel] = 20.6. The 'Feedstock Supply Logistics Process' section includes: feedstock amount [kg per kg ethanol] = 11.3. The 'Feedstock Handling and Preparation Process' section includes: electricity [kWh per kg of fuel] = 0.36. The 'IL Pretreatment Process' section is empty. A bar chart on the right shows 'Water Consumption' with a red box over it that says 'NOT ACCURATE DATA: EXAMPLE ONLY'.

Predict Minimum Selling Price and Greenhouse Gas Emissions

3 – Technical Progress: Initial property module output



- Use Fourier-transform infrared spectroscopy (FTIR) to correlate spectra to cetane number (CN)
- Demonstrated principle component regression and support vector machine regression to correlate IR spectra to octane number and low temperature combustion index
- Initial results show good correlation with cetane number
- Results can be interpreted unlike artificial neural networks

3 – Technical Progress: Initial LCA/TEA output

Select Output Molecule:

Common Parameters

GWP time horizon [years] = 100

biorefinery electricity source [region] = US

feedstock = Sorghum

ionic liquid = [Ch][Lys]

Feedstock Supply Logistics Process

feedstock amount [kg per kg ethanol] = 11.3

Feedstock Handling and Preparation Process

electricity [kWh per kg of fuel] = 0.36

IL Pretreatment Process

acid selection = H2SO4

electricity [kWh per kg of fuel] = 0.09

biorefinery steam low heat [kg per kg fuel] = 0.91

ionic liquid amount [kg per kg feedstock] = 0.01

acid [kg per kg ionic liquid] = 5.53

Enzymatic Hydrolysis and Fermentation Process

biorefinery cooling water [liters per kg fuel] = 221

biorefinery steam low heat [kg per kg fuel] = 0.69

cellulase amount [kg per kg cellulose] = 0.02

electricity [kWh per kg of fuel] = 5.58

corn liquor [g per kg fermentable sugars] = 0.21

inoculum [kg per kg fuel] = 0.03

diammonium phosphate [g per kg fermentable sugars] = 0.02

Recovery and Separation Process

electricity [kWh per kg of fuel] = 0.13

biorefinery cooling water [liters per kg fuel] = 152

biorefinery steam low heat [kg per kg fuel] = 9.59

biorefinery steam high heat [kg per kg fuel] = 20.6

Hydrogeneration and Oligomerization Process

cyclohexane [kg per kg fuel] = 0.01

electricity [kWh per kg of fuel] = 0.00

PdAC_catalyst [kg per kg fuel] = 0.00

hydrogen [kg per kg fuel] = 0.01

Trifluoroacetic [kg per kg fuel] = 0.01

biorefinery chilled water [liters per kg fuel] = 22.7

biorefinery steam low heat [kg per kg fuel] = 0.15

biorefinery cooling water [liters per kg fuel] = 1.82

cooling water 25oC [liters per kg fuel] = 0.62

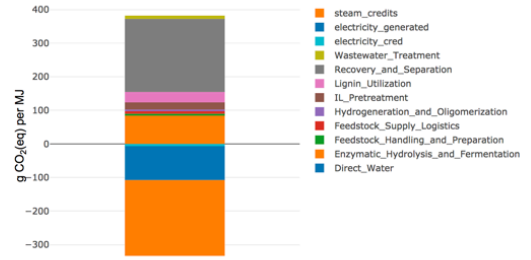
Wastewater Treatment Process

electricity [kWh per kg of fuel] = 0.40

WWT nutrients (lime) [kg per kg ethanol] = 0.00

biorefinery steam low heat [kg per kg fuel] = 0.76

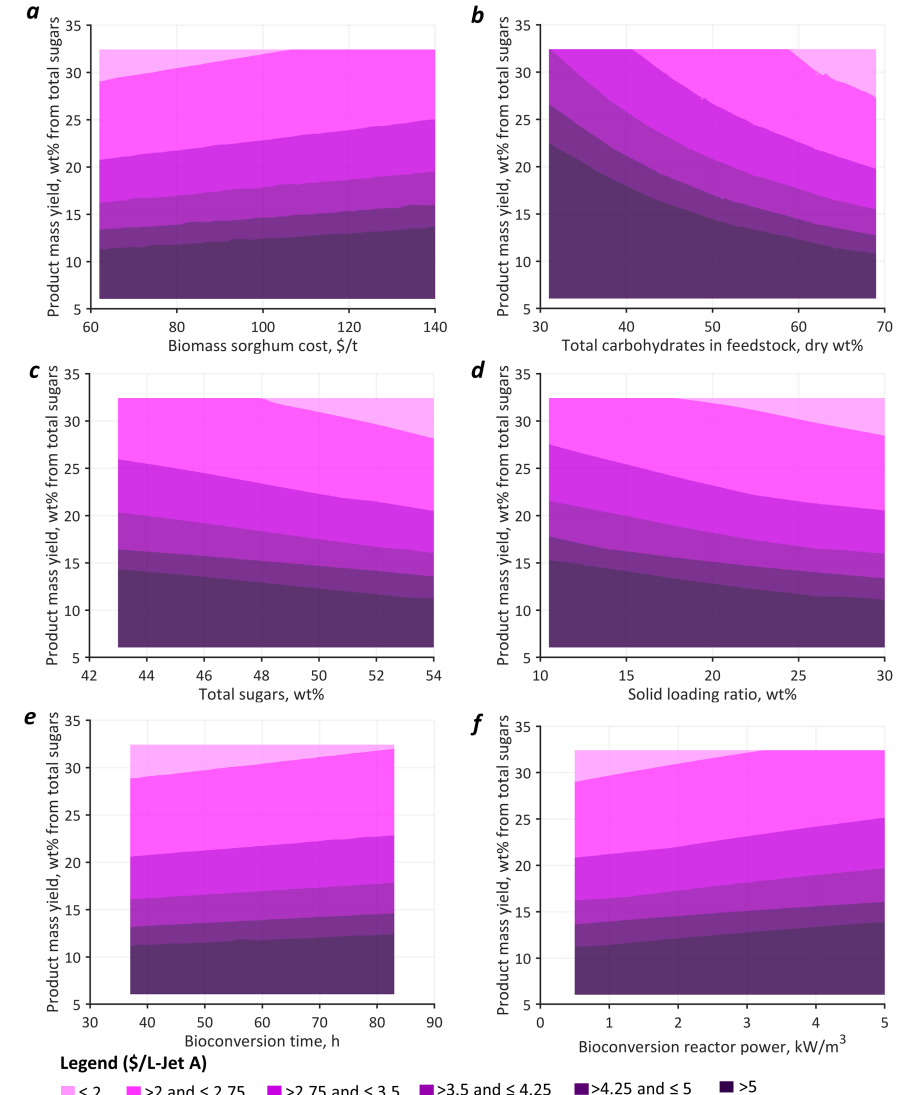
cip2 [kg per kg fuel] = 0.06



Sorghum → Limonene

- Completed TEA/LCA tool framework
- Generated results for biologically-produced limonene
- Conducted sensitivity analysis

Upgraded limonene cost sensitivity
 (Source: Baral et al 2019 Energy & Environmental Science)



4 – Relevance

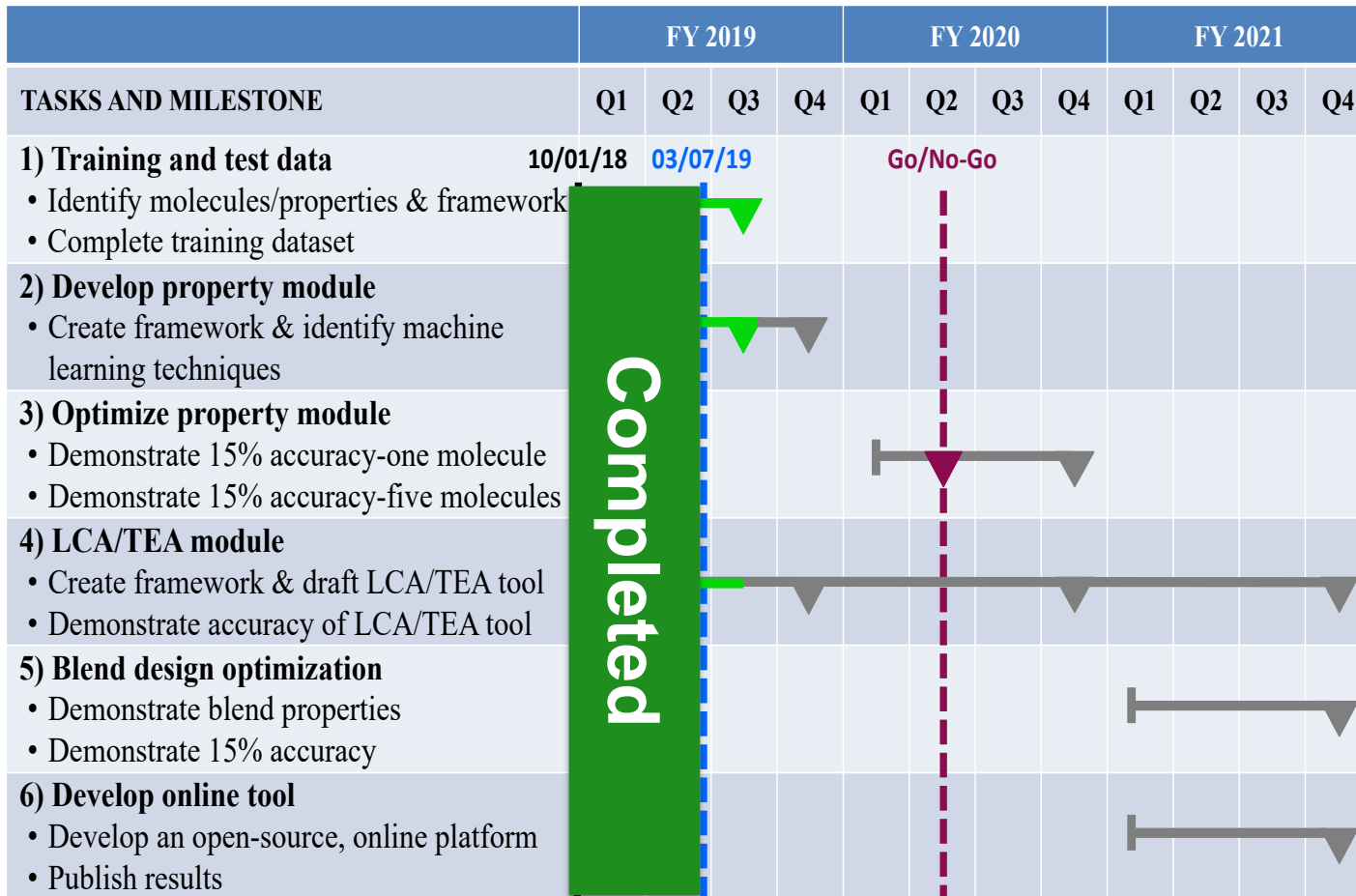
F2F is an open-source, online tool that will enable faster, less expensive bioprocess optimization, certification, and scale-up by predicting high value properties, MSP, and GHG emissions of new molecules and blends

- Supports DOE BETO Mission and Goals
 - “Develop and demonstrate transformative and revolutionary bioenergy technologies for a sustainable nation”
 - “Enable sustainable, nationwide production of biofuels that are compatible with today’s transportation infrastructure, can reduce greenhouse gas emissions relative to petroleum-derived fuels, and can displace a share of petroleum-derived fuels to reduce U.S. dependence on foreign oil”
 - “Encourage the creation of a new domestic bioenergy and bioproduct industry”
- Supports industry with making progress towards DOE BETO performance goal: \$3 per gallon gasoline equivalent (GGE) with GHG emissions reduction of 50% or more

4 – Relevance (continued)

- Supports ADO Mission and Goals
 - “De-risk bioenergy production technologies through validated proof of performance at the pilot, demonstration, and pioneer scales and to conduct activities that will transform the biofuels market by reducing or removing commercialization barriers.”
 - Complementary to aviation fuel efforts
- Addresses Multiple BETO Barriers
 - ADO-C. Codes, Standards, and Approval for Use
 - Ct-J. Identification and Evaluation of Potential Bioproducts
 - Ct-N. Multiscale Computational Framework toward Accelerating Technology Development
- Supports production of domestically produced biofuels that increase domestic energy security by reducing U.S. reliance on foreign oil, increase aviation resilience by introducing multiple fuel production pathways, and create jobs particularly in rural areas
- Project metrics and technical targets driven by industry targets

5 – Future Work

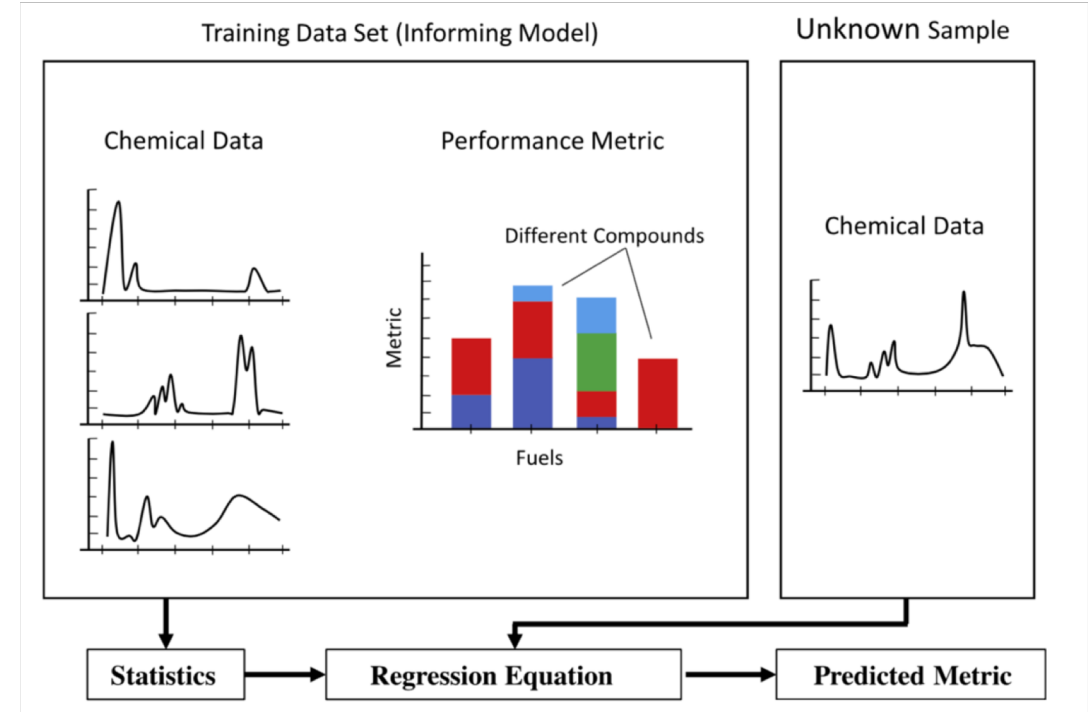
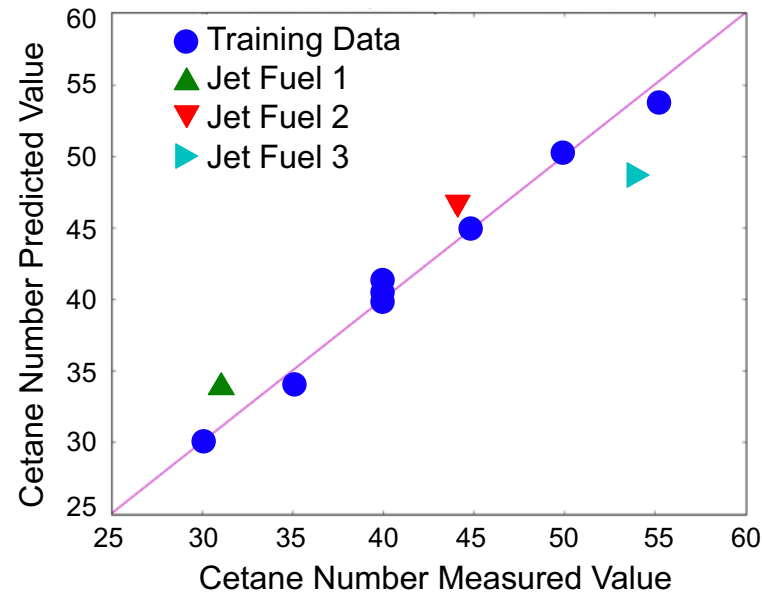


On schedule and within budget for remaining FY19 tasks

- Ahead of schedule on future milestones
 - Predicted minimum selling price (MSP) and GHG emissions from limonene
 - Predicted CN of three jet fuels as proof of concept
 - Created framework for online tool
- Continue development of ML algorithms using TPOT and `scikit.learn` to predict high priority properties
- Optimize tool to demonstrate prediction capabilities for Go/No-Go decision

5 – Future Work: Expand property module

- Expanded properties to include:
 - Alternative jet fuel certification properties
 - High priority industry identified properties



Flow chart from Daly et al. Fuel 183 (2016) 359–365

- Test and optimize using:
 - Previously ASTM certified alternative jet fuels
 - Industry molecules with sufficient experimental data

5 – Future Work: Expand and validate LCA/TEA module

Select Output Molecule:

Limonene

Run GHG Model

Run Cost Model

Use Default Values

Use SuperPro Values

Common Parameters

GWP time horizon [years] = 100

biorefinery electricity source [region] US

feedstock = Sorghum

ionic liquid = [Ch][Lys]

Feedstock Supply Logistics Process

feedstock amount [kg per kg ethanol] = 11.3

Feedstock Handling and Preparation Process

electricity [kWh per kg of fuel] = 0.36

IL Pretreatment Process

acid selection = H2SO4

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biorefinery steam low heat

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biorefinery cooling water

[liters per kg fuel] = 221.

biorefinery steam low heat

Recovery and Separation Process

electricity [kWh per kg of fuel] = 0.13

biorefinery cooling water

[liters per kg fuel] = 152.6

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biorefinery steam high heat

[kg per kg fuel] = 20.6

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[kg per kg fuel] = 0.00

hydrogen

[kg per kg fuel] = 0.01

Trifluoroacetic

[kg per kg fuel] = 0.01

biorefinery chilled water

[liters per kg fuel] = 22.7

biorefinery steam low heat

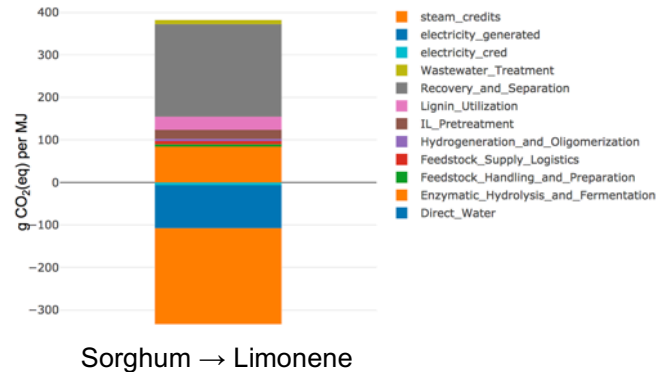
[kg per kg fuel] = 0.15

biorefinery cooling water

[liters per kg fuel] = 1.82

cooling water 25oC

[liters per kg fuel] = 0.62



- Expand to include:
 - Previously ASTM certified alternative jet fuels
 - Add most relevant feedstocks for each fuel
 - At least 2-3 biomass deconstruction options
 - Relevant upgrading processes as needed
 - GHG and cost impact of use-phase property differences (e.g. density, LHV)

Summary

1. **Goal:** developing a flexible, open-source tool that predicts properties of high-potential molecules (fuels, fuel co-products, and other bioproducts) derived from biomass and evaluate the cost, benefits, and risk of promising biobased molecules or biofuels to enable faster, less expensive bioprocess optimization, certification, and scale-up
2. **Approach:** Leverage machine learning (ML) to predict desired properties and LBNL expertise to develop a lightweight TEA/LCA tool. Use alternative jet pathways and other well characterized molecules to validate ML algorithms
3. **Progress:** Predicted cetane number of a few jet fuels and estimated minimum selling price (MSP) and GHG emissions from limonene; developed framework for online tool; initiated database with 400+ different molecules and blends; initiated evaluation of ML techniques for property prediction; and confirming with industry high-priority molecules and properties for database.
4. **Relevance:** Aligns with DOE BETO goals and addresses multiple barriers (ADO-C, Ct-J, and Ct-N)
5. **Future work:** Expand, optimize, and validate property and LCA/TEA modules

Project Team

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ADDITIONAL SLIDES

Risk Registry Table

		Risk Identified		Mitigation Strategy		Current Status
Risk ID	Process Step	Risk Description	Severity (High/Med/Low)	Mitigation Response	Planned Action Date	Active/Closed
Training Dataset Properties						
1	FY19Q3	Properties for training dataset are incomplete, contain multiple different entries, or molecules are too few to accurately train tool	Low	Select most common value (median) or average values for multiple entries; for missing entries, we will leave them open for the tool to predict or replace property with alternative desired property	6/30/2019	Active
Machine learning algorithm						
2	FY19Q4	Machine learning algorithm unable to predict properties to within 15%	Med	Will minimize risk by considering a wide breadth of algorithms and through optimization to achieve desired accuracy	9/30/2019	Active
High computational resources						
3	FY19Q4	Computational needs exceed resources	Low	Will optimize tool to reduce computational time for predicting properties and seek out additional computing resources	9/30/2019	Active
TEA Algorithm						
4	FY21Q4	Lightweight TEA methods prove unreliable in predicting mass/energy balances and costs	Low	Will use SuperPro Designer to provide reliable cost estimates and isolate key sources of non-linear effects that can be accounted for in other ways	9/30/2021	Active

Example: View Existing Database Properties



Explore Property Database

Design Blends

Predict Properties

Predict Cost and GHG Footprint

by SMILES CC1=CC[C@@H](CC1)C(=C)C Search

Names and Identifiers **Properties** Available Blends

Property	Value	Source
Mel	74.35 °C	Scifinder
Boiling Point		Scifinder
Density	0.8402 g/cm ³	Scifinder
RON	87.1	2009, SNL
DCN	19.0	
Heat of Vaporization	289.95 kJ/kg	Predicted ACDB
MON	76	Predicted property using F2F on 10/10/2019

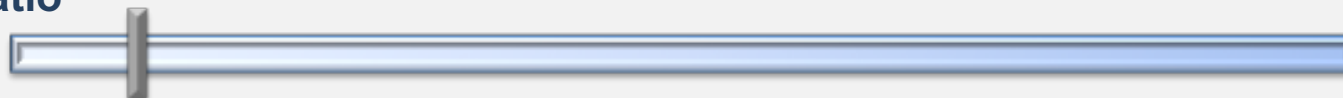
NOT ACCURATE DATA: EXAMPLE ONLY



Example: Predict properties of blends

[Home](#)[About](#)[Tools](#)[Data Sources](#)[Documentation](#)[References](#)[Explore Property Database](#)[Design Blends](#)[Predict Properties](#)[Predict Cost and GHG Footprint](#)Select Molecule by SMILES

blended with

Blend Ratio

Molecule

Jet A

Predicted Blend Properties

Property	Predicted Value	Accuracy	Algorithm
Boiling Point			
Density*	0.8402 g/cm ³		
DCN	44.3	+/- 0.6	Predicted by volume %
Heat of Vaporization	289.95 kJ/kg		Predicted by D labs Chempider

NOT ACCURATE DATA: EXAMPLE ONLY

* Predicted without measured neat properties