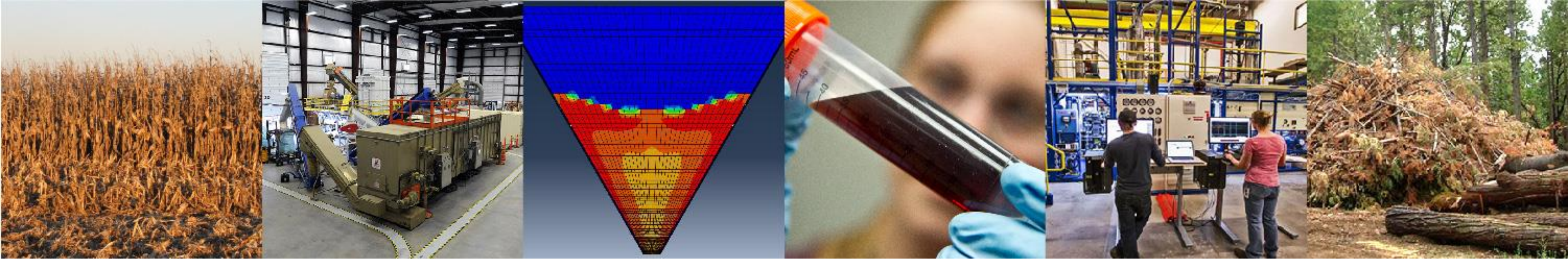


DOE Bioenergy Technologies Office (BETO) 2019 Project Peer Review

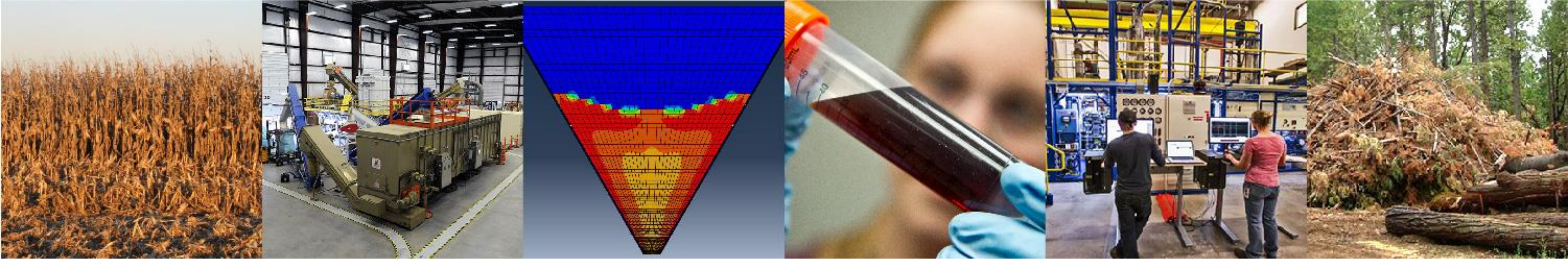
System-wide Throughput Analysis

WBS 2.2.1.601-605

March 7, 2019

PI: David N. Thompson (INL)

Lab Leads: Mary Biddy (NREL)
Steven Phillips (PNNL)
Michael Wang (ANL)
Erin Webb (ORNL)



Goal of the Consortium

Identify and address the impacts of feedstock variability – chemical, physical, and mechanical – on biomass preprocessing and conversion equipment and system performance, to move towards 90% operational reliability.

Goal Statement

PROJECT GOALS

- Develop an operational reliability metric that goes beyond classical time-driven reliability and utilization approaches to include feedstock property-driven impacts
- Integrate disparate modeling approaches to model operational reliability and utilize FCIC experimental data to provide modeled baseline benchmarks for two preprocessing-conversion systems

OUTCOMES

- Relevant reliability metrics that capture the impacts of feedstock quality on system productivity and yield
- Modeled baseline benchmarks to understand where we are starting and to track R&D progress toward BETO targets

RELEVANCE TO THE BIOENERGY INDUSTRY

- Recent evidence indicates that IBR development and operation have suffered from failing to account for the complexity and variability of lignocellulosic biomass and their impacts to reliably achieving design capacity and yield, and hence productivity

Quad Chart Overview

Timeline

- Project Start Date: Nov. 2017
- Project End Date : Dec. 2018 (anticipated)
- Percent Complete: 100%

	Total Costs Pre FY17**	FY 17 Costs	FY 18 Costs	Total Planned Funding (FY 19-Project End Date)
DOE Funded	N.A.	$0	$658.2K	$0
Project Cost Share*	N.A.	N.A.	N.A.	N.A.

- **Partners**

Partners on this project include INL (57.0%), ANL (6.8%), NREL (12.0%), ORNL (15.6%), and PNNL (8.5%)

Barriers addressed

- Ct-J. Process Integration
- Ft-I. Overall Integration and Scale-Up
- Ft-J. Operational Reliability
- It-C. Technical Risk of Scaling

Objective

- Develop a unique, dynamic, integrated system-wide approach to model operational reliability, which is a new metric for which no current modeling methodology exists

FY18 Project Goals

- Establish and coordinate the FCIC R&D activities so that the baseline activities and materials generated can be metricized and used as the benchmark to compare and establish future R&D performance objectives
- Determine modeled baseline reliabilities for two process designs and their respective distributions of feedstock properties, over a year of simulated operation

1 – Project Overview

Feedstock Variability and Specification Development
Allison Ray (INL)

Feedstock Physical Performance Modeling
Tyler Westover (INL)

Biomass Quality

Process Integration
Ed Wolfrum (NREL)

Upstream-Downstream Process Integration

System-wide Throughput Analysis
Dave Thompson (INL)

Process Control and Optimization
Quang Nguyen (INL)

System Readiness Evaluation

Characterizing Biomass & Mining Data

Improving Operational Performance

Implementing Integrated Control Strategies

1 – Project Overview (continued)

HISTORY/CONTEXT

- Discrete event simulation (DES) for supply logistics based on IBSAL models
- DES for preprocessing & feeding based on FY17 Go/No-go (WBS 1.1.1.2)
  - 1.1.1.2 simulation results were consistent with the learnings of the DOE Tiger team
- Process simulations
  - Low-temperature conversion based on 2011 ethanol design report
  - High-temperature conversion based on 2013 uncatalyzed fast pyrolysis design report

OBJECTIVES

- Define operational reliability metric that captures system-wide feedstock variability impacts
- Model the operational reliability of two systems, one low-temperature (LT) and one high-temperature (HT) and develop operational reliability baseline benchmarks

CREATIVE ADVANTAGE

- Classical reliability and utilization are both based on operating time, and lack a connection to actual production achieved…which is tied to economic performance
- Current modeling methodologies cannot simultaneously capture feedstock variability impacts to dynamic throughput and yield
- Our models can be used to estimate the impact of feedstock property changes and system changes using What-if Analysis

2 – Approach (Management)

MANAGEMENT APPROACH

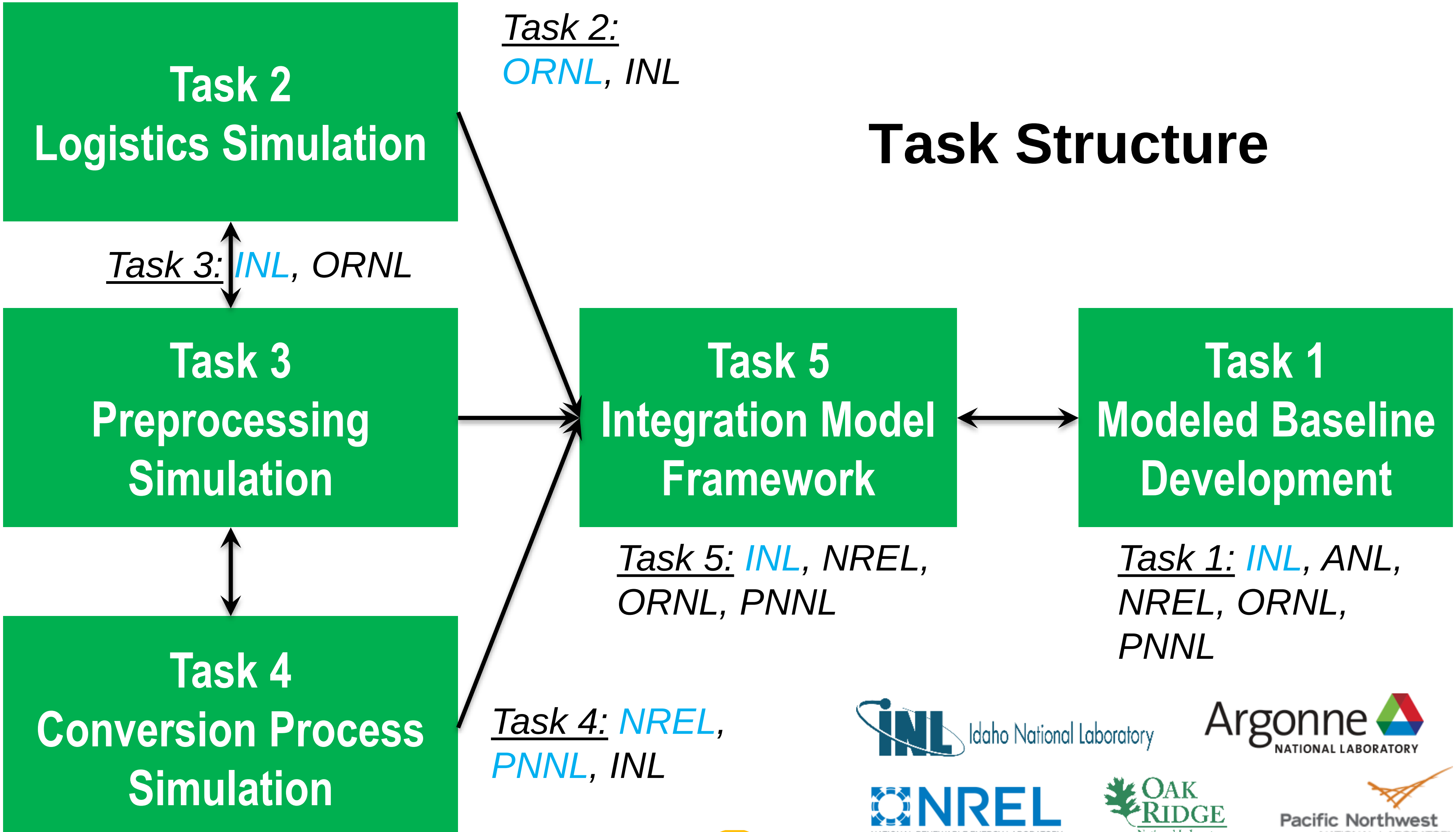
- Data collection and alignment through FCIC R&D projects, peer-reviewed literature & prior BETO-funded R&D results
- Engage FCIC Industry Advisory Board to clarify differences in large-scale impacts vs. National Lab process development unit (PDU) impacts (e.g., down times resulting from failures)
- Collaborate across the FCIC projects to include all data and results
- Bi-weekly conference calls with BETO
- Bi-weekly team coordination calls (INL, ANL, NREL, ORNL, PNNL)
- Three Quarterly Progress Milestones
- One Annual (SMART) milestone for high-impact deliverables and outcomes

TEAM MEMBERS AND FOCUS

- Logistics DES: Erin Webb (ORNL), Damon Hartley (INL)
- Preprocessing and Conversion DES: Damon Hartley (INL)
- LT Process Simulation: Mary Biddy, Ryan Davis, Andrew Bartling (NREL)
- HT Process Simulation: Sue Jones, Steve Philips (PNNL), Abhijit Dutta (NREL)
- LCA/Sustainability: Michael Wang, Hao Cai, P. Thatiana Benevides (ANL)

2 – Approach (Management)

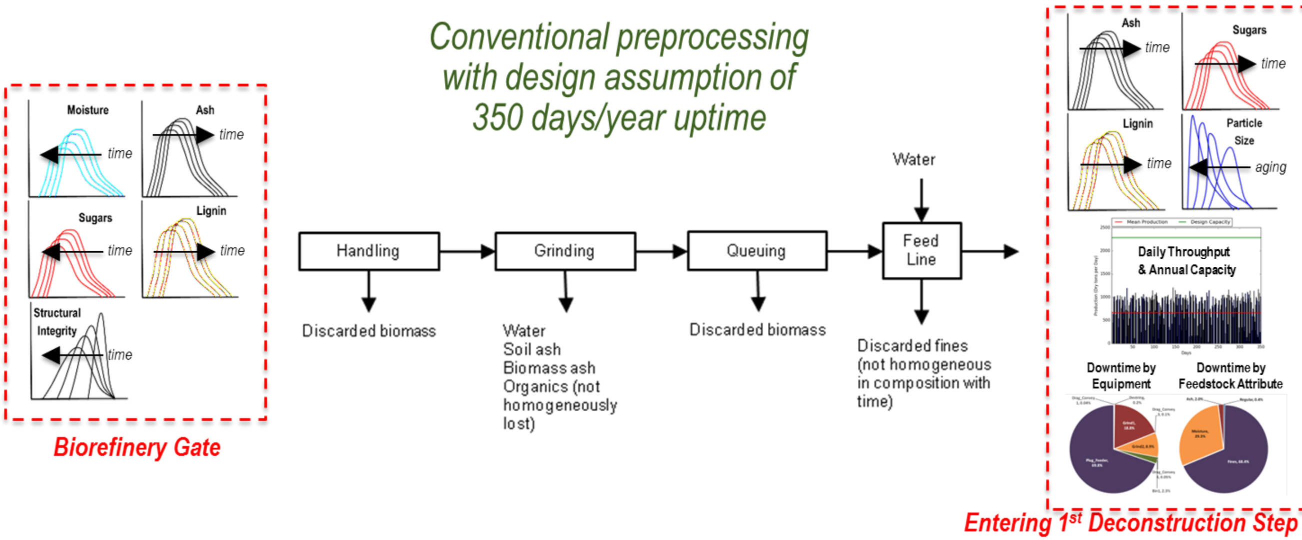
Task Structure



2 – Approach (Technical)

GENERAL APPROACH – DISCRETE EVENT SIMULATION (DES)

- Baselines developed from dynamic TEA models that utilized DES of complete PDU systems (not individual equipment)
- DES based on frequency and type of PDU operator interventions during experimental baselining



- The preprocessing and conversion PDUs were modeled individually due to lack of peer-reviewed scaling information for PDU to pioneer biorefinery scale (hence, did not estimate scaled biorefinery costs)
- Based on available data from experimental baselining in FY18, modeled integrated-PDU annual throughput, yield and operational reliability only for the LT PDU system (throughput only for HT PDU system)

2 – Approach (Technical) (continued)

- **Daily and Annual Feedstock Throughput into Deconstruction**
  - T_i = Daily throughput of biomass into the first deconstruction step on day *i* (dry tons)
  - T_N = Annual biomass feedstock capacity of the biorefinery (dry tons)
- **Daily and Annual Conversion Performance**
  - $Y_{i,90\%}$ = Daily yield of biofuel/ton of feedstock on day *i* (gal/ton) at design throughput
  - $Y_{N,90\%}$ = Annual biofuel yield/ton of feedstock of the biorefinery (gal/ton) at design throughput
- **Daily and Annual Biofuel Yield**
  - Y_i = Daily yield of biofuel on day *i* (gallons)
  - Y_N = Annual biofuel capacity of the biorefinery operation (gallons)
- **Daily and Annual Operational Cost**
  - $C_{i,OPEX}$ = Daily operating cost of the biorefinery on day *i* ($)
  - $C_{N,OPEX}$ = Annual operating cost of the biorefinery ($)
- **Profitability (i.e., net revenue)**
  - P_N = Net annual profit from producing the biofuel over the year (dollars)
  - FSP_{ave} = Average biofuel selling price over the year (dollars/gallon)

$$T_N = \sum_{i=1}^{N} T_i \qquad Y_{N,90\%} = \sum_{i=1}^{N} Y_{i,90\%} \qquad Y_N = \sum_{i=1}^{N} Y_i \qquad C_{N,OPEX} = \sum_{i=1}^{N} C_{i,OPEX}$$

$$P_N = FSP_{ave} \times Y_N - C_{N,OPEX} - C_{D,CAPEX}$$

2 – Approach (Technical) (continued)

SYSTEM-WIDE TECHNICAL AND ECONOMIC METRICS

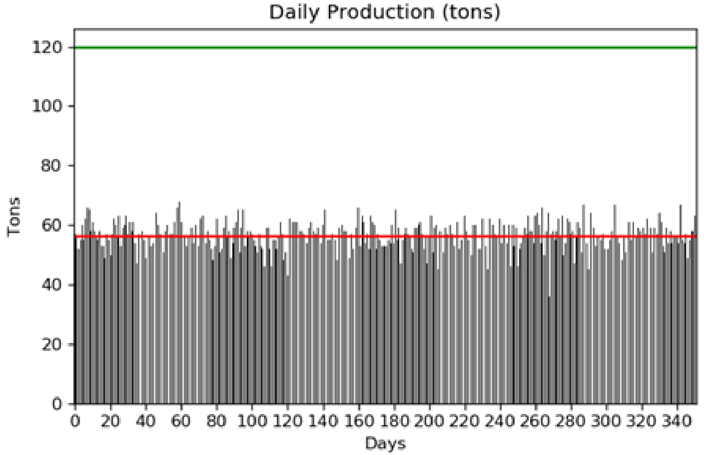
METRIC	DEFINITION
Annual Throughput Capacity Factor	$F_f = \frac{T_N}{T_D}$
Annual Biofuel Performance Factor	$F_B = \frac{Y_{N,90\%}}{Y_D}$
Operational Reliability	$R_{sys} = F_f \times F_B$
Annual Biorefinery Profitability Factor	$F_P = \frac{P_N}{P_D}$

- **Throughput factor** captures the impacts of physical and mechanical feedstock attributes on feedstock throughput capacity utilization
- **Biofuel performance factor** captures the impacts of compositional and structural feedstock attributes on average conversion performance
- **Operational reliability** captures the net overall impact of feedstock attributes on biofuel productivity
- **Profitability factor** captures the composite impacts of feedstock attributes on net costs

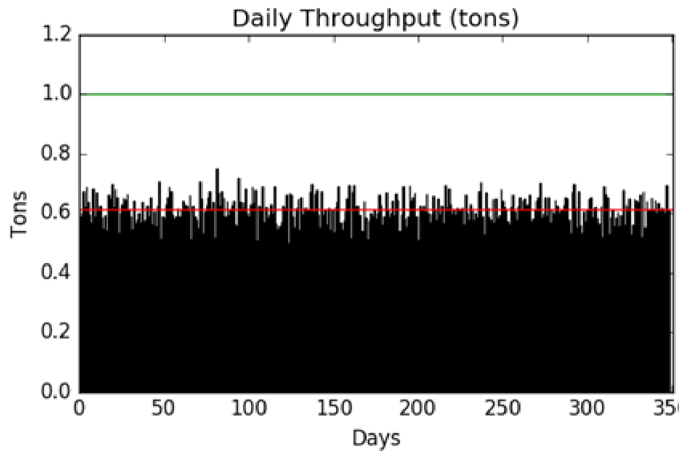
2 – Approach (Technical) (continued)

- **DES Models**
  - Modeled individual PDUs at the system level
    - INL Preprocessing PDU (2 models)
    - NREL pretreatment PDU
    - NREL pyrolysis PDU
  - Utilized frequency of operator interventions and operator-supplied time off-stream provided by PDU teams
  - Model outputs
    - Preprocessing – Dynamic and cumulative annual throughput, particle size, moisture, ash and convertible organics entering conversion
    - Pretreatment – Dynamic and cumulative annual pretreatment throughput
    - Pyrolysis – Dynamic and cumulative annual pyrolysis throughput

LT Preprocessing DES



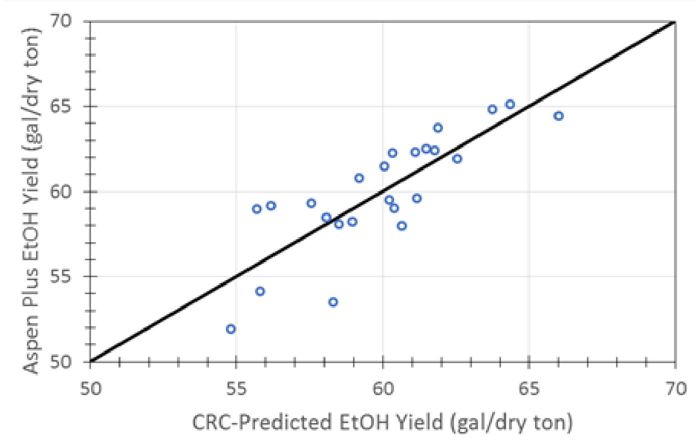
LT Conversion DES



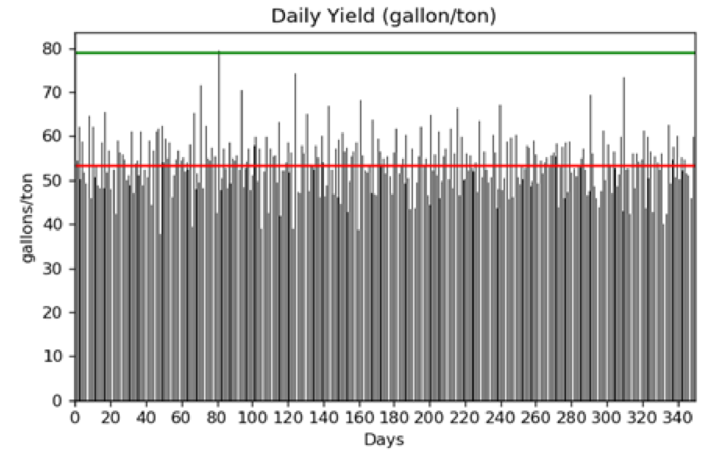
2 – Approach (Technical) (continued)

- **Conversion Response Correlations**
  - Existing process models
    - 2011 ethanol design report
    - 2013 uncatalyzed fast pyrolysis design report
  - Modified to allow variable input compositions and yields
  - Compositional and yield data from the experimental PDU baselining runs
  - Model outputs
    - Predicted dynamic biofuel yields as functions of feedstock property inputs
- **Integrated DES & CRC**
  - Model outputs
    - Dynamic and cumulative annual biofuel production

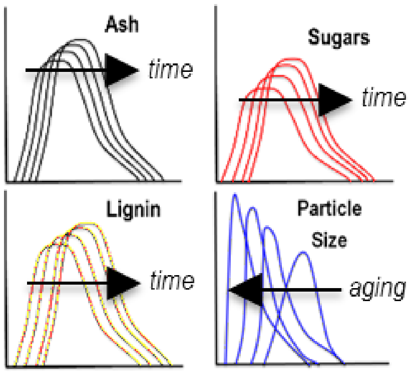
LT CRC

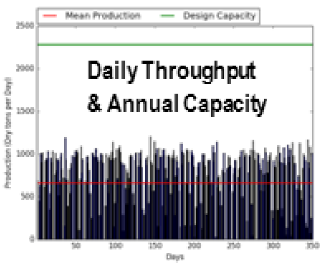


LT: Coupled DES/CRC

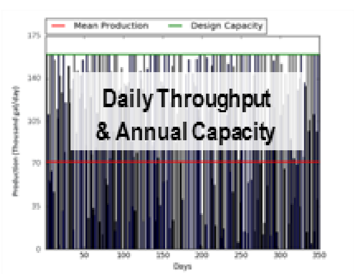


2 – Approach (Technical)





Preprocessing



Conversion

TOP 3 TECHNICAL CHALLENGES

- Integrating disparate models and approaches for different parts of the system into credible dynamic system-wide reliability models
- Lack of prior R&D datasets purposely measured to determine operational impacts
- Lack of understanding of how to scale PDU data up to commercial-scale models

CRITICAL SUCCESS FACTORS

- Technical
  - Vetted datasets across representative ranges of feedstock attributes
  - Inclusion of biorefining experts' and operators' inputs regarding impacts, magnitudes and scaling
  - Fundamental understanding of mechanisms of impacts to equipment and/or subsystems
- Business – Effective dissemination of results to industry

3 – Technical Accomplishments/ Progress/Results (continued)

COMPARISON OF MODELED THROUGHPUT TO LOW-TEMP EXPERIMENTAL

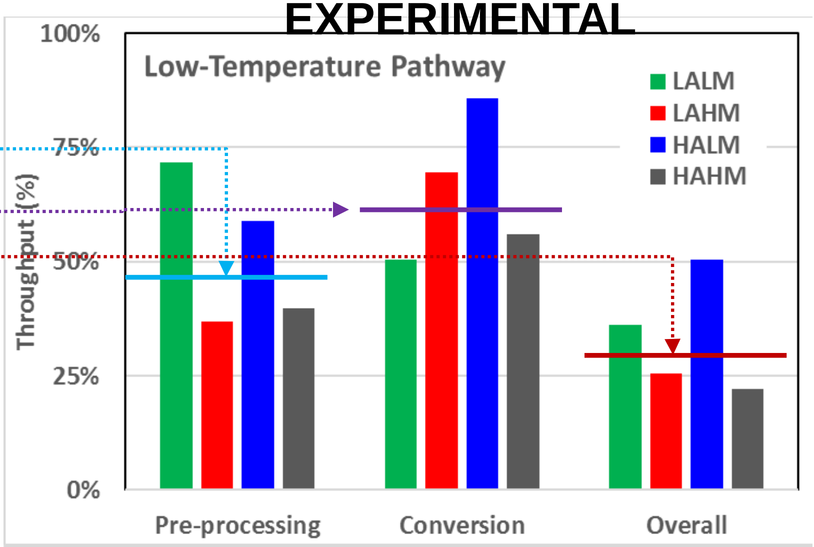
<u>Modeled Throughput, 1 yr operation</u>

Pre-processing: $F_{f,INL\ Low\text{-}temp} = 47.1\%$

Conversion: $F_{f,NREL\ Low\text{-}temp} = 61.5\%$

Overall: $F_{f,Overall\ Low\text{-}temp} = 29.0\%$

EXPERIMENTAL



ACCOMPLISHMENT

- Integrated the available PDU and sampling data from the four low-temperature experimental baselining runs into the two low-temperature DES models
- Simulated one year of operation for the distributions of feedstock moisture, ash and convertible organics used in the experimental baselining
- Successfully modeled operational reliability, evidenced by replicating the Low-temp experimental results

IMPACT

- Modeled capacity utilization represents the expected performance over long-term operation given property distributions
- We now have a Low-temp modeling framework that can be updated and expanded to new technologies as needed to support the FCIC

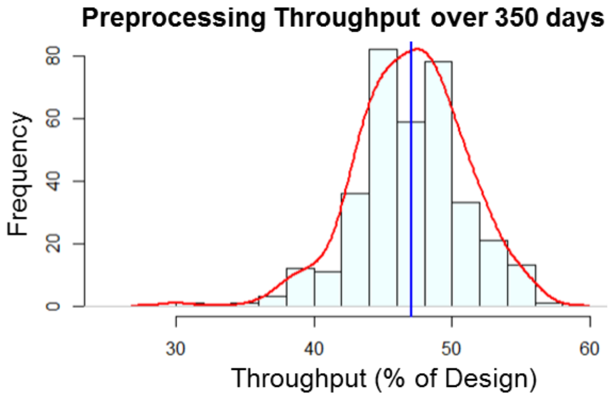
3 – Technical Accomplishments/ Progress/Results

FY18 GOAL: LOW-TEMPERATURE MODELED BASELINE FOR FCIC

- Ties together Low-temp information/data from all other FCIC activities
- Provides a bridge to quantify the implications around economics/LCA metrics

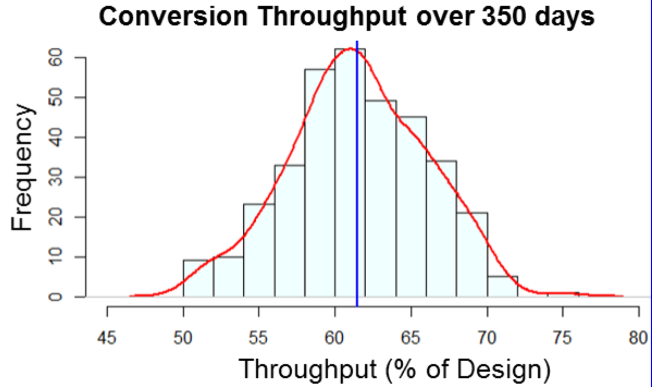
Preprocessing Throughput Capacity Factor

$F_{f,INL\ Low\text{-}temp} = 47.1\%$



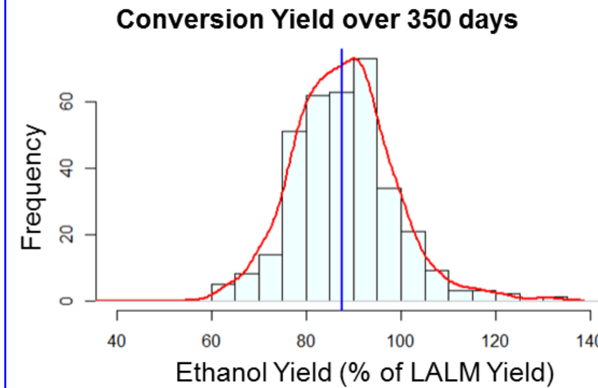
Conversion Throughput Capacity Factor

$F_{f,NREL\ Low\text{-}temp} = 61.5\%$



Conversion Performance Factor

$F_{B,Low\text{-}temp} = 88.1\%$



- **Operational Reliability:** $R_{sys,Low\text{-}temp} = F_{f,INL\ Low\text{-}temp} \times F_{f,NREL\ Low\text{-}temp} \times F_{B,Low\text{-}temp} = 25.5\%$
- **GHG Emissions:** Preprocessing = 15.462 kg CO_2e / dry ton feedstock
  Scaled conversion = 1.935 kg CO_2e / gal ethanol

3 – Technical Accomplishments/ Progress/Results (continued)

- **MODELED LOW-TEMPERATURE CONVERSION DOWNTIME**

ACCOMPLISHMENT

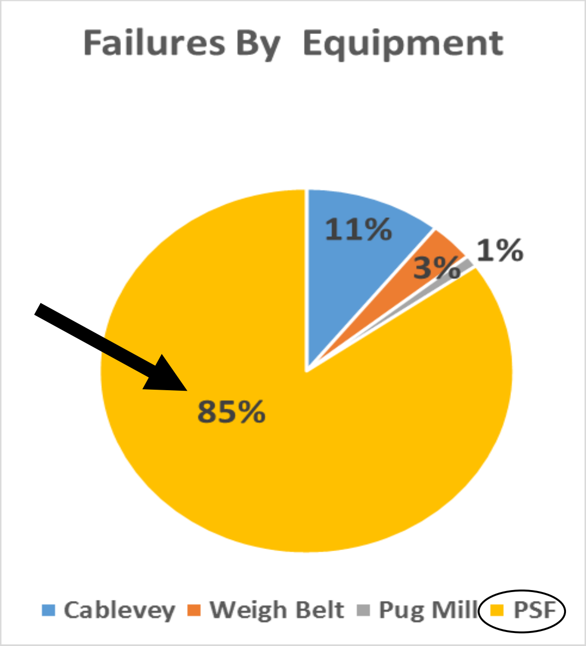
- Prediction of Low-temp equipment operational impacts over long-term
- Based on experimental baselining frequency of occurrence and on feedstock properties in the system

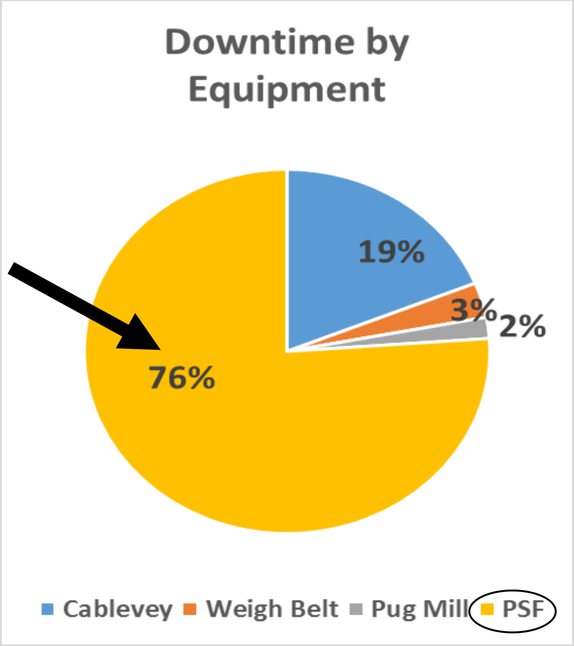
IMPACT

- Targets individual Low-temp equipment as more or less impactful
- Provides sensitivity of operation to feedstock variation (informed by property distributions)

Modeled 350 days of operation

	Failure Rate (occurrences/hr)	MTTF (min)	Down Time (min)
Cablevey	0.14	422	20
Weigh Belt	0.05	1,277	10
Pugmill	0.01	4,286	40
Plug Screw Feeder	1.71	35	20





3 – Technical Accomplishments/ Progress/Results (continued)

COMPARISON OF MODELED THROUGHPUT TO HIGH-TEMP EXPERIMENTAL

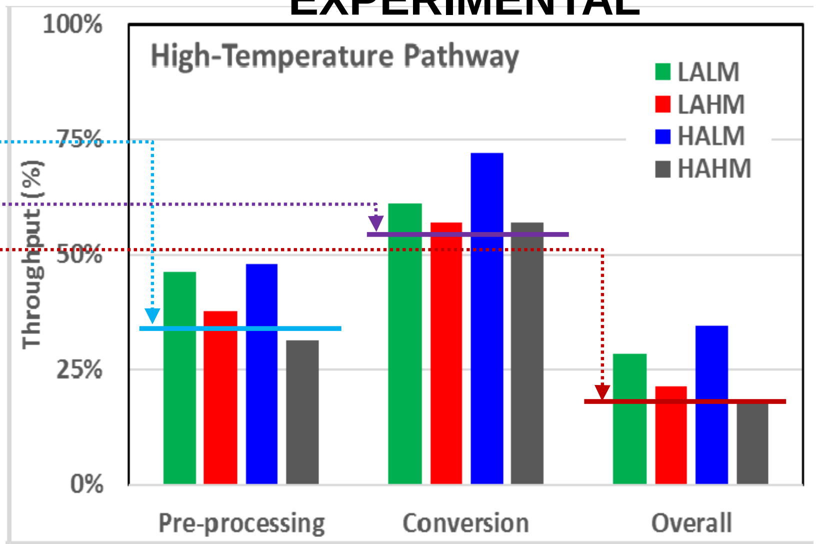
Modeled High-Temp Throughput

Pre-processing: $F_{f,INL\ High\text{-}temp} = 33.6\%$

Conversion: $F_{f,NREL\ High\text{-}temp} = 54.7\%$

Overall: $F_{f,Overall\ High\text{-}temp} = 18.4\%$

EXPERIMENTAL



ACCOMPLISHMENT

- Integrated the available PDU and sampling data from the four high-temperature experimental baselining runs into the two high-temperature DES models
- Simulated one year of operation for the distributions of feedstock moisture, ash and convertible organics used in the experimental baselining
- Successfully modeled operational reliability, evidenced by replicating the High-temp experimental results

IMPACT

- Modeled capacity utilization represents the expected performance over long-term operation given property distributions
- We now have a High-temp modeling framework that can be updated and expanded to new technologies as needed to support the FCIC

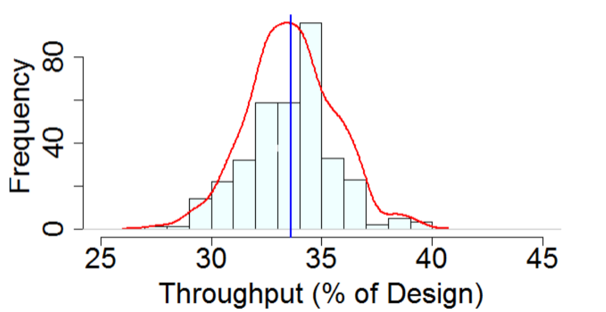
3 – Technical Accomplishments/ Progress/Results (continued)

FY18 GOAL: HIGH-TEMPERATURE MODELED BASELINE FOR FCIC

– Ties together High-temp information/data from all other FCIC activities
– Provides a bridge to quantify the implications around economics/LCA metrics

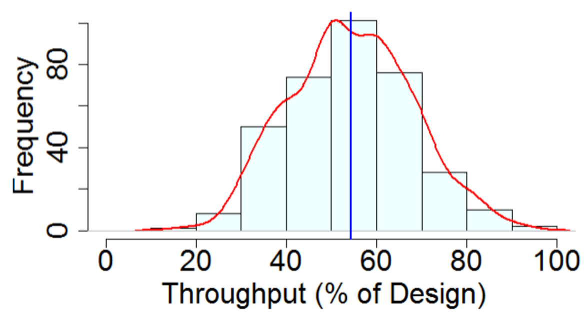
Preprocessing Throughput Capacity Factor

$F_{f,INL\ High\text{-}temp}$ = 33.6%



Conversion Throughput Capacity Factor

$F_{f,NREL\ High\text{-}temp}$ = 54.7%



Conversion Performance Factor

$F_{B,High\text{-}temp}$ = 100% (assumed)

Conversion Yield over 350 days

Due to sample backlogs from the HT PDU baselining runs, sufficient data were not completed by the end of FY18 to develop an HT CRC

- **Operational Reliability:** $R_{sys,High\text{-}temp} = F_{f,INL\ High\text{-}temp} \times F_{f,NREL\ High\text{-}temp} \times F_{B,High\text{-}temp}$ = 18.4%
- **GHG Emissions:** Preprocessing = 182.92 kg CO_2e / dry ton feedstock
  Scaled conversion = Not determined

3 – Technical Accomplishments/ Progress/Results (continued)

- **MODELED HIGH-TEMPERATURE CONVERSION DOWNTIME**

ACCOMPLISHMENT

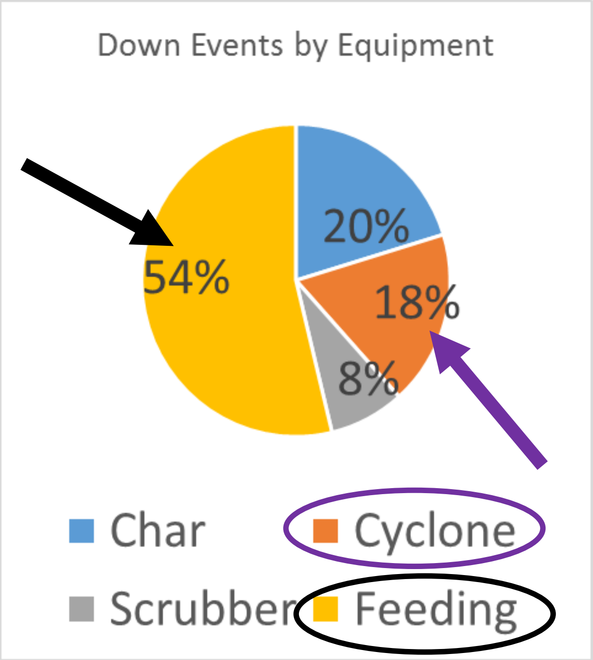
- Prediction of High-temp equipment operational impacts over long-term
- Based on experimental baselining frequency of occurrence and on feedstock properties in the system

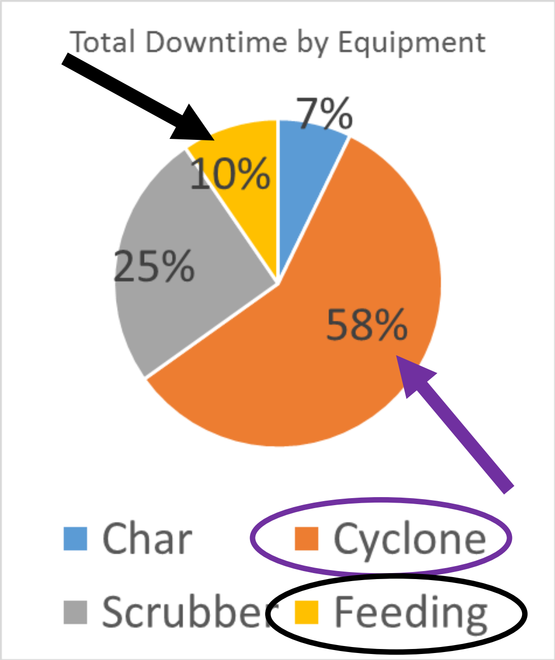
IMPACT

- Targets individual High-temp equipment as more or less impactful
- Provides sensitivity of operation to feedstock variation (informed by property distributions)

Modeled 350 days of operation

	Failure Rate (Occurrences/hr)	MTTF (min)	Down Time (min)
Feed Train	0.32	184.8	10
Cyclones	0.08	739.2	180
Char system	0.16	369.6	20
Scrubber	0.05	1,108.8	180





4 – Relevance

PRODUCTS AND OUTPUTS

- Integrated models for modeling reliability
- Low-temperature Integrated PDU baseline
- High-temperature Integrated PDU baseline

CUSTOMERS

- FCIC R&D projects and the FCIC as a whole
- Future customers will include technology and system developers

INTENDED USE BY CUSTOMERS

- Assessment of system impacts of potential technology solutions for feedstock supply and quality barriers to expanding the bioenergy industry

INDUSTRY ENGAGEMENT

- Data collection on operational impacts at pioneer biorefinery scales
- Potential for trade-off analyses to understand cost-effective solutions to pioneer biorefinery operational issues

Summary

KEY TAKEAWAYS

OVERVIEW

- This project provides system-level technoeconomic assessment, integrating experimental results from both preprocessing and conversion to estimate the relative magnitudes of feedstock property impacts to throughput, yield, productivity, cost and sustainability

APPROACH

- Discrete event simulation and process models were developed and integrated to examine the full impact of feedstock properties on dynamic throughput, yield and annual performance

ACCOMPLISHMENTS

- Demonstrated the validity of DES modeling approach to reliability
- Modeled baselines, based on a year of simulated operation, were developed based on experimental baselining runs

RELEVANCE

– Provides a objective method of assessment for proposed process improvements in the context of a biofuel production system

Questions?


Source: http://karenshulman.com/portfolio-view/running-effective-meetings/

Thank You

fcic.inl.gov

Response to Reviewers' Comments 2017

- This project was not reviewed in the 2017 Peer Review. The initial DES analysis that led to this analysis (WBS 1.1.1.2 Go/No-go Decision Point) was FY17 work scope (future work) for that project at the time of the 2017 Peer Review.

Publications

- None yet for this project.

Presentations

- None yet for this project.

SUPPORTING SLIDES FOR PRESENTATION

Approach – Management (continued)

TASK	LEAD
Task 1: Baseline development	D. Thompson (INL)
Task 2: Feedstock supply logistics discrete event simulation development *<u>Subtask 2.1:</u> Corn Stover Logistics DES* *<u>Subtask 2.2:</u> Corn Stover Storage DES* *<u>Subtask 2.3:</u> Pine Residue Logistics DES*	E. Webb (ORNL) *E. Webb (ORNL)* *D. Hartley (INL)* *E. Webb (ORNL)*
Task 3: Feedstock preprocessing discrete event simulation development *<u>Subtask 3.1:</u> Preprocessing DES* *<u>Subtask 3.2:</u> Code migration to ExtendSim®*	D. Hartley (INL) *D. Hartley (INL)* *D. Hartley (INL)*
Task 4: Conversion modeling and development *<u>Subtask 4.1:</u> Low Temperature (Biochemical)* *<u>Subtask 4.2:</u> High Temperature (Thermochemical)*	M. Biddy (NREL) *M. Biddy (NREL)* *S. Phillips (PNNL)*
Task 5: Integration of models, framework development and system-wide analysis	D. Thompson (INL)

Classical Approach to Improving Productivity

- **Reliability** is the ability of a piece of equipment to consistently perform its intended or required function or mission, on demand and without degradation or failure
  - Classical reliability is defined as

$$R = e^{-\left(\frac{Scheduled\ Time}{Mean\ Time\ Between\ Failures}\right)}$$

  - It is a measure of the probability that the equipment will fail and not be available
- **Utilization** is the ratio of time spent by a piece of equipment on productive efforts to the total time consumed

$$U = \left(\frac{Working\ Time}{Scheduled\ Time}\right)$$

- Both measures are based on time, and lack a connection to actual production achieved, which is tied to economic performance
- We focused on **Throughput Analysis** because it can be used to directly estimate the **Capacity Utilization** and **Economics** of the overall system

Focused on Discrete Event Simulation to Estimate Annual System Capacity Utilization

- **Primary Purpose of Modeled Baselines**
  - Estimate annual integrated PDU system capacity utilization as a function of frequency of observed operator interventions and expected time off stream
  - Estimate annual conversion performance as a function of feedstock properties
  - Estimate "**operational reliability**", which is a function of both throughput and conversion performance
  - Estimate annual biofuel production and profitability
- **Definitions**
  - **Modeled Annual Throughput Capacity**
    - F_f = Modeled throughput capacity utilization factor (%)
    - T_D = *Pro forma* design annual throughput capacity of the biorefinery (tons)

$$F_f = \frac{T_N}{T_D}$$

  - **Modeled Annual Biofuel Performance**
    - F_B = Modeled biofuel production performance factor (%)
    - Y_D = *Pro forma* design annual biofuel capacity of the biorefinery (gal/ton)

$$F_B = \frac{Y_{N,90\%}}{Y_D}$$

  - **Modeled Annual Biorefinery Profitability**
    - F_P = Modeled biorefinery profitability factor (%)
    - P_D = *Pro forma* design annual net revenue of the biorefinery (dollars)

$$F_P = \frac{P_N}{P_D}$$

The Mathematical Definitions of Operational Reliability and the Modeled Baselines

- **Operational reliability is a measure of overall system performance**
  - R_{sys} = Modeled operational reliability of the biorefinery gate to fuel biorefining system (%)

$$R_{sys} = F_f \times F_B$$

Provides a composite metric with which to gauge FCIC progress toward the integration of preprocessing and conversion into a system that can operate at or more closely to the pro forma design scenarios' assumed times on-stream

- **Definition of Baselines**
  - Comprised of the modeled values of the capacity utilization factors, profitability factor and the modeled operational reliability, individually for the baseline low-temperature and high-temperature systems

$$F_{f,baseline} = \frac{T_{N,baseline}}{T_D} \qquad F_{B,baseline} = \frac{Y_{N,baseline}}{Y_D} \qquad F_{P,baseline} = \frac{P_{N,baseline}}{P_D}$$

$$R_{sys,baseline} = F_{f,baseline} \times F_{B,baseline}$$

3 – Technical Accomplishments/ Progress/Results

GAP ANALYSIS OF BIOREFINING OPERATIONAL KNOWLEDGE

- Focused on soliciting Subject Matter Expert (SME) inputs on feedstock property impacts on individual equipment/unit operations across the field-to-biofuel system

ACCOMPLISHMENT

- System-wide SME knowledge database of impact of high-level feedstock attributes on individual equipment performance and yield
- SMEs hypothesized a large number of potential failure modes and impacts
  - Low-temp system: 347 entries
  - High-temp system: 211 entries
- Working with the R&D projects, prioritized attributes & impacts based on available funding and ability to measure

IMPACT

- First-of-a-kind system-wide repository of biorefining SME operational knowledge
- Identifies what is currently known and where gaps exist in the knowledge base

QUESTIONNAIRE

COLUMN HEADING	WHAT IS BEING REQUESTED
Value-Chain Element	Range within the field-to-biofuel value chain, e.g., Harvest through to entry into field-side storage.
Operation	Individual operation within the value chain element, e.g., harvest, field drying, collection, etc. For conversion it breaks down by plant area.
Factor	Environmental factors, feedstock attributes, etc. that cause impacts to throughput, composition or conversion yield within the operation.
Trigger Value of Factor	What range, value or level of the Factor triggers a process upset, stoppage, or change in throughput, composition or conversion yield?
Trigger Value Units	Units for the Trigger value
Throughput, composition or conversion yield Impacted?	Is the process impact that ultimately occurs on the throughput, composition or intermediate yield of the operation?
Impacted equipment	What specific equipment within the operation is/are impacted?
Impacted attribute or processing operation	Feedstock attribute or process parameter that is impacted by the factor, e.g., moisture content, particle size, grinding energy, etc.
Impact Occurrence relative to Trigger	Does the impact occur when the factor is above, equal to, or below the trigger value of the Factor?
Impact	Increase/decrease/fail throughput, increase/decrease specific feedstock attribute or property, or increase/decrease intermediate yield? This is the dependent variable that is needed for the modeling. At this point it is listed as increase/decrease/fail, but for the baseline continuous functions (for increases/decreases) or discrete values (for failures) will be needed to be collected during Q2 and the first 2 months of Q3.
Impact units	Units for the Impact
Discrete Impact or Continuous Function	Is the impact a discrete value or a continuous function of one or more parameters?
Impact is Function of	If continuous function, what does the function depend on? These are the independent variables necessary to vary during measurement.
Measurement Method (reference, or source if anecdotal)	Measurement method used for impact magnitude, or source and basis/scale of information if anecdotal industry operational information.
Standard Deviation of Impact Magnitude	Is there variance information available for purposes of sensitivity analysis?
Expected Probability of Occurrence (H/M/L)	What is the expected probability that the Factors leading to this Impact will occur, i.e. High (> 75%), Medium (25% -75%), or Low (< 25%)
Expected Severity to of Impact to Throughput, Composition or Yield (S/I/U)	What is the expected severity of the Impact to throughput, composition or yield within the operation, i.e. Significant, Insignificant, or Unknown
Notes	Descriptive notes on known or predicted impact(s) of the factor.

EXAMPLE RESULT (LOW-TEMP)

"Particle Size/Range - DMA Properties impacts Throughput of the pretreater by causing a/an decrease in the throughput at values _____ _____ _____. The impact is a _____ function of History, pretreatment, UV, age, moisture. Data are available from: _____, and the impact range is _____." NOTES: Decreased flowability due to viscoelastic properties.