

# *The Feedstock-Conversion Interface Consortium – Understanding and Mitigating the Impacts of Feedstock Variability in Bioconversion Processes*

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**U.S. DEPARTMENT OF ENERGY** 



# *1-slide guide to the FCIC*

The Feedstock-Conversion Interface Consortium is led by DOE as a collaborative effort among researchers from 9 National Labs

### **Key Ideas**

- Biomass feedstock properties are **variable** and **different** from other commodities
- **Empirical** approaches to address these issues have been **unsuccessful**

The FCIC uses **first-principlesbased science to de-risk** biorefinery scale-up and deployment by understanding and mitigating the impacts of **feedstock variability** on bioenergy conversion processes.





<http://energy.gov/fcic>

























# *FCIC Task Organization*

**Task 8: TEA/LCA**







**Task 3: Materials Handling**



**Task 4: Data Integration**

**Task X: Project Management**

**Task 3: Materials Handling: Develop tools that enable** continuous, steady, trouble free feed into reactors

**Task 1: Materials of Construction:** Specify materials that do not corrode, wear, or break at unacceptable rates

**Task 5: Preprocessing: Enable well-defined and** homogeneous feedstock from variable biomass resources

**Task 2: Feedstock Variability:** Quantify & understand the sources of biomass resource and feedstock variability

**Task 4: Data Integration:** Ensure the data generated in the FCIC are curated and stored – FAIR guidelines

**Task 6 & 7: Conversion (High- & Low-Temp Pathways):**  Produce homogeneous intermediates to convert into marketready products



**Task 8:Crosscutting Analyses TEA/LCA:** Valuation of intermediate streams & quantify variability impact















**Task X: Project Management:** Provide scientific leadership and organizational project management





## *Quantifying Effects of Variability to Assess Risk*

- An example using low-temperature conversion
	- –Corn stover Feedstock
	- –Deconstruction with Deacetylation & Mechanical Refining and Enzymatic Hydrolysis (DMR/EH)
	- –Upgrading Sugars to mixed organic acids, lignin monomers to muconate
- **How does corn stover variability present a risk to biorefineries?**





#### **Organisms**

#### **Facilities**

#### **Products**

![](_page_3_Picture_15.jpeg)

Rhodosporidium toluloides

![](_page_3_Picture_17.jpeg)

![](_page_3_Picture_18.jpeg)

Zymomonas nobilis

Pseudomonas

Clostridium

yrobutyricun

![](_page_3_Picture_20.jpeg)

![](_page_3_Figure_21.jpeg)

![](_page_3_Figure_22.jpeg)

![](_page_3_Picture_23.jpeg)

![](_page_3_Figure_24.jpeg)

![](_page_3_Picture_25.jpeg)

![](_page_3_Picture_26.jpeg)

### *Feedstock Variability is an Economic Risk*

**Analysis courtesy of Ryan Davis (NREL)**

![](_page_4_Figure_10.jpeg)

![](_page_4_Picture_11.jpeg)

### **Risk ~ slope and shape of the lines**

![](_page_4_Picture_8.jpeg)

### **COMPOSITION COST CONVERTIBILITY**

![](_page_4_Figure_2.jpeg)

![](_page_4_Picture_5.jpeg)

140% 130% MFSP (\$/GGE)<br>MFSP 120%<br>E 110% 100% 90% \$70 \$80 \$90 \$100 60% 80% 65% 70% 75% **Biomass Feedstock Cost (\$/ton) Glucan/Xylan EH Conversion (% of theor.)** 

5

## *Composition Variability is a Risk*

**Effect of corn stover compositional variability on minimum ethanol selling price (MESP),** *Bioresource Technology 140:426 (2013), Tao et al,* <https://doi.org/10.1016/j.biortech.2013.04.083>

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![](_page_5_Figure_1.jpeg)

![](_page_5_Picture_7.jpeg)

### *Conversion Variability is a Risk*

![](_page_6_Figure_1.jpeg)

**Data courtesy of Xiaowen Chen (NREL), analysis courtesy of Ryan Davis (NREL)**

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# *Quality by Design*

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![](_page_7_Picture_3.jpeg)

# *Quality by Design (QbD) to Assess Risk*

![](_page_8_Figure_11.jpeg)

![](_page_8_Picture_12.jpeg)

![](_page_8_Picture_13.jpeg)

- Key operating concept and organizing principle
- Widely used in pharmaceutical manufacturing – FDA-endorsed
- Chemical processes are collections of specific unit operations
- Unit operations are discrete but  $\frac{1}{2}$ connected
- Need fundamental understanding of
	- Unit operation
	- Input & Output streams

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# **Moving from feedstock NAMES to feedstock ATTRIBUTES**

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![](_page_9_Picture_6.jpeg)

hayandforage.com

![](_page_9_Picture_9.jpeg)

![](_page_9_Picture_10.jpeg)

# *QbD for the Biomass Value Chain*

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![](_page_10_Figure_1.jpeg)

- **CQAs**:
	- Soluble Sugar Content
- Residual substrates
- Inhibitors

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![](_page_10_Figure_11.jpeg)

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![](_page_10_Picture_3.jpeg)

![](_page_10_Picture_4.jpeg)

erature e Loading ence Time

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# *Representative Accomplishments*

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### *Review Article: Flow Behavior Characterization of Biomass Feedstocks*

- Existing powder processing/handling equipment are mostly designed for coal and pharmaceutical ingredients, rather than for biomass
- Biomass encounters flow stoppages in these repurposed equipment, hampering process economics
- Lack of knowledge on the unique flow behavior of biomass feedstocks

#### **Current Knowledge Gap**

#### **Achievement**

- **Discussed** how powder flow behavior depends on the inherent properties, the environment, and the processing equipment
- **Reviewed** literature on the characterization of biomass powder flow behavior using shear testers and powder rheometers
- **Proposed** complementing powder rheometry with surface energy measurements, tribometry and DEM modeling to better understand the flow behavior of biomass powders

#### **Industry Impact**

This review article educates audiences working on powder flow characterization in both industrial and academic settings, and provides them with insights on future research directions

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![](_page_12_Picture_31.jpeg)

**It's imperative to test each powder because the flow behavior of a powder is determined by its inherent properties, the environment, and the processing unit it's in.** 

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![](_page_12_Picture_9.jpeg)

#### *Task 3 – Material Handling*

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![](_page_12_Figure_28.jpeg)

![](_page_12_Figure_29.jpeg)

![](_page_12_Picture_30.jpeg)

Flow Behavior Characterization of Biomass Feedstocks. Powder Technology (2021) 387, 156-180, DOI: [10.1016/j.powtec.2021.04.004](https://doi.org/10.1016/j.powtec.2021.04.004)

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## *Continuum Modeling of Hopper Flow*

### **Current Knowledge Gap**

- The mechanical flow behavior of compressible pine chips is not systematically investigated
- Flowing pine chips through hopper experiences inconsistence manifested as hopper arching, rat-holing, and surging flow

### **Achievement**

The knowledge can be directly applied to prepare the charging process of wedge-shaped hopper and to operate hopper in terms of inclination angle and outlet opening for handling pine chips.

![](_page_13_Picture_14.jpeg)

- Conducted **physical experiments** and **numerical simulations** to investigate the influence of pine CMAs and hopper CPPs on hopper flow performance.
- Found hopper outlet width linearly controls the mass flow rate while the hopper inclination angle controls the critical outlet size.
- Found feedstock initial packing determines whether the flow is smooth or surging, and the surcharge-induced compaction creates flow impedance.

### **Industry Impact**

### **Investigated pine CMAs & Hopper CPPs on mass flow rate and critical arching width using experimental data validated continuum-model**

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![](_page_13_Picture_24.jpeg)

Flow and Arching of Biomass Particles in Wedge-Shaped Hoppers, ACS Sustainable Chemistry & Engineering (2021) 9:45, 15303–15314, [DOI:10.1021/acssuschemeng.1c05628](https://doi.org/10.1021/acssuschemeng.1c05628)

![](_page_13_Picture_4.jpeg)

## *Real-Time Feedstock Image Analysis Model*

#### **Description**

• Utilized a 26,000 image dataset from processing corn stover in a pretreatment reactor captured using **inexpensive digital cameras**.

Machine Learning Methods - Neural Network (NN) and Pixel Matrix Feature Parameterization (PMFP) used to analyze data

#### **Value of new tool**

- Neural Network (NN) model can detect anomalies (coarseparticle segregation that can cause feed interruption) even when camera lens obscured by dust.
- PMFP method reveals statistically significant image textural features such as surface roughness, shade variations, and particle angular direction variations that are proxies for particle size distribution variation.
- NN and PMFP approaches are complementary to one another and can describe why feedstock images are classified a certain way.

![](_page_14_Picture_17.jpeg)

### **Automated machine vision technique detects and quantifies corn stover feedstock particle quality in real-time to enable process control**

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<sup>1</sup>conical feed-hopper cyclically refilled every ~30 min

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**Tools**

Real-Time Biomass Feedstock Particle Quality Detection Using Image Analysis and Machine Vision. <http://dx.doi.org/10.1007/s13399-020-00904-w>

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**MFSP**: Minimum Fuel Selling Price; **FP**: Fast Pyrolysis; **CFP**: Catalytic Fast Pyrolysis; **TEA**: Techno-Economic Analysis

### *Computational Framework For High-Temperature Modeling – CFD to TEA*

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Machine learning (ML) style regression analysis develops correlations for evaluation in process modelling software (e.g., Aspen Plus)

**Task 6 – High Temperature Conversion** 

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Process

Feedstock CMAs

**Eedstock** 

![](_page_15_Figure_6.jpeg)

![](_page_15_Figure_3.jpeg)

A simplified integrated framework for predicting the economic impacts of feedstock variations in a catalytic fast pyrolysis conversion process <https://doi.org/10.1002/bbb.2319>

**Combining Particle-, Reactor-, and Process models facilitates rapid TEA assessments of feedstock and process variability** 

## Key Take-Aways

- **Feedstock variability** across the Bioenergy Value Chain is a Risk to **Biorefineries**
- **FCIC** Researchers are using elements of the **Quality -by -Design** approach to understand and mitigate the impacts of **feedstock variability** on bioenergy conversion processes.
- Deep subject matter expertise, detailed chemical, physical, and mechanical characterization, and robust and validated modeling is providing **knowledge and tools** to bioenergy stakeholders

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#### **U.S. DEPARTMENT OF ENERGY**

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