INTEGRATED PROCESS OPTIMIZATION FOR BIOCHEMICAL CONVERSION

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OUTLINE

RESEARCH MOTIVATION

OPPORTUNITIES:

- U.S. federal agencies have funded scientific research in the field of bioenergy in order to:
  - Develop transformative bioenergy technologies.
  - Enhance national biofuel production to reduce dependencies on foreign oil.
  - Initiate the creation of a sustainable domestic bioeconomy.
- DOE identifies the optimization of biomass feeding system as critical for consistent throughput of conversion processes (DOE, 2016)[1]
  - Consistent throughput at the conversion process is vital to reduce the cost of bioenergy.

1 U.S. Department of Energy, DOE. 2016. Biorefinery optimization workshop summary report.

RESEARCH MOTIVATION

CHALLENGES:

- Variation in biomass characteristics result in inconsistent feeding rates and conversion yields.
  - Particle size (diameter)
  - Particle shape
  - Particle density
  - Moisture content
  - Ash content

- Fine particles with high moisture content cause plugging of equipment.
- Different types of unprocessed biomass have different densities, which impacts process flow.
- Biorefineries carry inventory due to seasonal biomass supply.
  - Storage adversely affects the chemical composition of the biomass.

BIOMASS FEEDING PROCESS OPTIMIZATION

RESEARCH OBJECTIVE:

The goal of this research is to reduce the cost of producing biofuels by designing a reliable, cost effective, sustainable, robust system for feeding of biomass feedstocks to the reactor.

EXPECTED RESEARCH OUTCOMES:

1) An optimized feeding system design - from biomass grinding to the reactor throat - which ensures reactor reliability nearly 90% for biomass with 10-30% moisture and 5-15% ash contents.
2) Successful integration of biomass feeding and conversion processes.

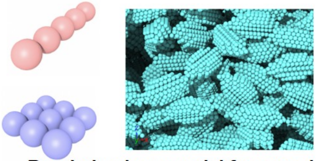
METHODOLOGY:

- Use Discrete Element Method models to predict material flowability and equipment performance for different feedstock types.
- Develop mathematical models which optimize the performance of the system give biomass characteristics and equipment performance.

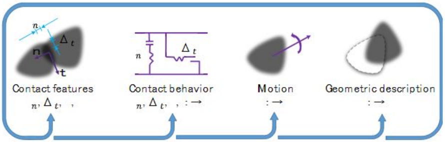
DISCRETE ELEMENT METHOD:

Discrete Element Method (DEM) is a numerical method used to model bulk behaviour of granular particles.

- Bonded-sphere DEM models are used capture complex particle shapes, realistic size distribution, and particle deformability.
- Liquid bridge DEM models are used capture moisture effect on plugging in equipment.



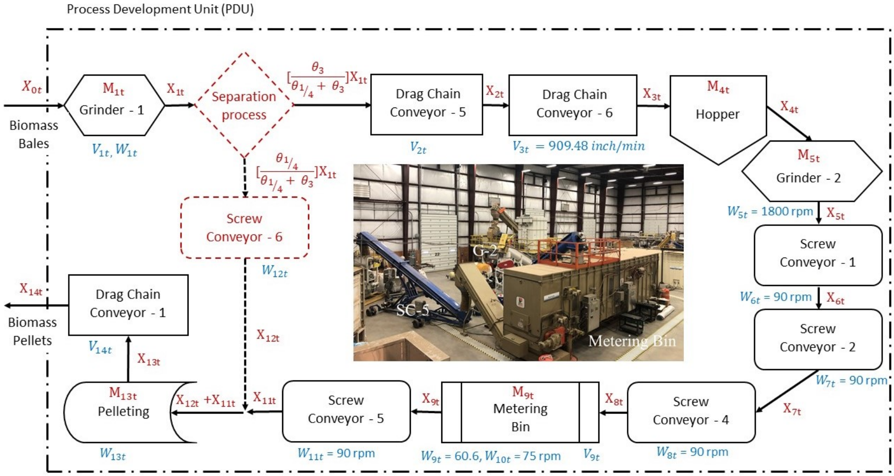
Bonded-sphere model for complex-shaped deformable particles



A typical DEM computation cycle

IDAHO NATIONAL LABORATORY (INL) - PROCESS DEVELOPMENT UNIT

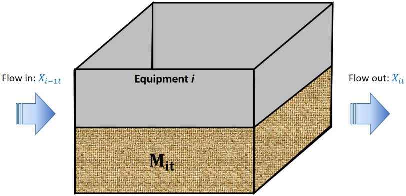
The figure summarizes the different processes at INL's process development unit.



DECISION VARIABLES

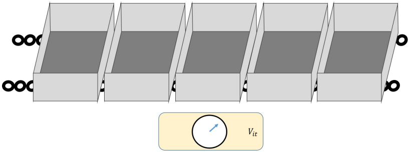
BIOMASS FLOW AND INVENTORY HOLDING DECISIONS:

- X_{0t} Amt. of biomass fed to the system in period t
- X_{it} Amt. of biomass flowing from equipment i in period t
- M_{it} Inventory held in equipment i in period t

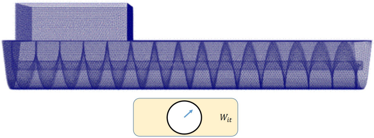


EQUIPMENT SETTING DECISIONS:

- V_{it} Speed of belt i in period t.



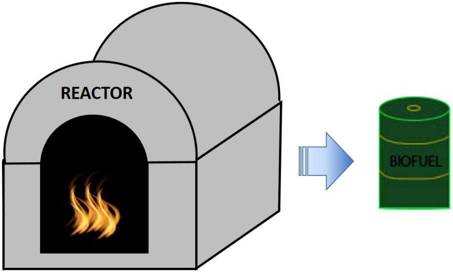
- W_{it} Rotational velocity of conveyor i in period t.



OBJECTIVE FUNCTION

- Let k represents the equipment which feeds the reactor.
- Objective Function:
  Minimize the maximum deviation from reactor's targeted feeding rate R in each period $t = 1, \ldots, T$.

$$\min_{X,V,W} \max_{t \in T} |R - X_{kt}|$$



BIOMASS FLOW TO GRINDER 1

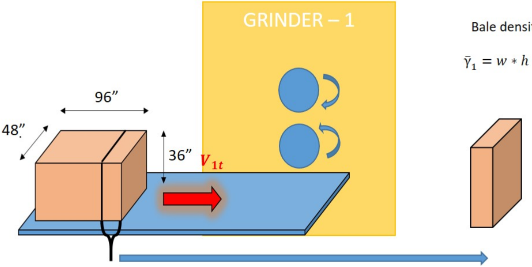
INPUTS:

- $w, h, \tilde{d}$ represent the width (inch), height (inch) and density (tons/$inch^3$) of a bale.

MATHEMATICAL MODEL:

- $\tilde{\gamma}_1$ represents the average mass (tons) of biomass per inch of conveyor belt. Thus, $\tilde{\gamma}_1 = w \times h \times \tilde{d}$ (tons/inch).

$$
\begin{aligned}
1(inch/min) \leq \quad V_{1t} \quad &\leq 32(inch/min) && (1)\\
X_{0t}(tons/min) \quad &\leq \quad \tilde{\gamma}_1(tons/inch)V_{1t}(inch/min) && (2)
\end{aligned}
$$



Bale density (d) ≈ $3.42 \cdot 10^{-6}$ tons/inch

$$
\begin{aligned}
\bar{\gamma}_1 = w * h * d &= 48 * 36 * 3.42 \cdot 10^{-6}\\
&= 5.92 \cdot 10^{-3} \text{ tons/inch}
\end{aligned}
$$

BIOMASS FLOW TO GRINDER 1

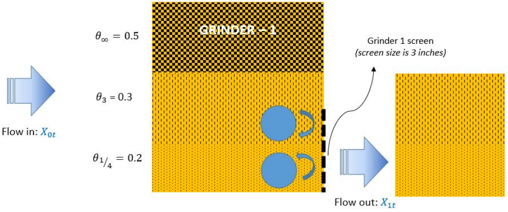
MATHEMATICAL MODEL:

- Let the flow from the grinder 1, during period t be X_{1t}.

$$X_{1t} \leq X_{0t} \qquad \forall t \in T. \tag{3}$$

- Biomass particles have random particle size (diameter).

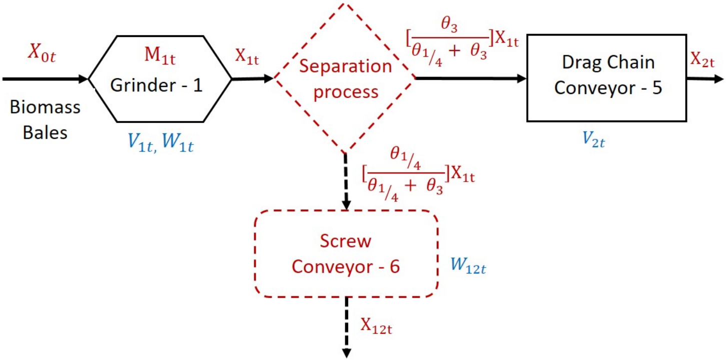
$$f_1(\tilde{d}^p) = \begin{cases} \theta_{\frac{1}{4}} & \text{for } d^p \in (0, \frac{1}{4}], \\ \theta_3 & \text{for } d^p \in (\frac{1}{4}, 3], \\ \theta_\infty & \text{for } d^p \in (3, \infty). \end{cases}$$



BIOMASS FLOW FROM GRINDER 1

SEPARATION PROCESS AFTER GRINDER 1:

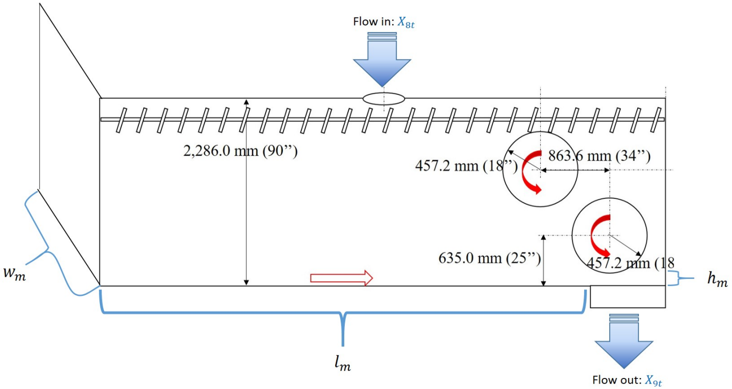
- Grinding increases the amount of fine particles which plug the system.
- Biomass with particle size [0", 1/4"] goes to pelleting.
- Biomass with particle size [1/4", 3"] goes to Grinder 2.



BIOMASS FLOW FROM METERING BIN

INPUTS:

- Metering bin geometry (l_m, w_m, h_m)
- Bulk density of the biomass, $\hat{d}$.



BIOMASS FLOW FROM METERING BIN

MATHEMATICAL MODEL:

- Flow from metering bin depends on the speed of belt conveyor and inventory level.

$$
\begin{aligned}
0 \leq V_{it} &\leq \overline{V_{it}} && \forall t \in T, && (4)\\
X_{it} &\leq \frac{(M_{it-1} + X_{i-1t})}{l_m} \times V_{it} && \forall t \in T, && (5)\\
X_{it} &\leq \hat{d} \times w_m \times h_m \times V_{it} && \forall t \in T, && (6)\\
X_{it} &\leq (M_{it-1} + X_{i-1t}) && \forall t \in T, && (7)
\end{aligned}
$$

- Mass conservation constraints:

$$
M_{it} = M_{it-1} + X_{i-1t} - X_{it} \qquad \forall t \in T, \qquad (8)
$$

- Storage capacity constraints:

$$
M_{it-1} + X_{i-1t} \leq \overline{M_i} \qquad \forall t \in T. \qquad (9)
$$

DATA ANALYSIS

PARTICLE SIZE DATA:

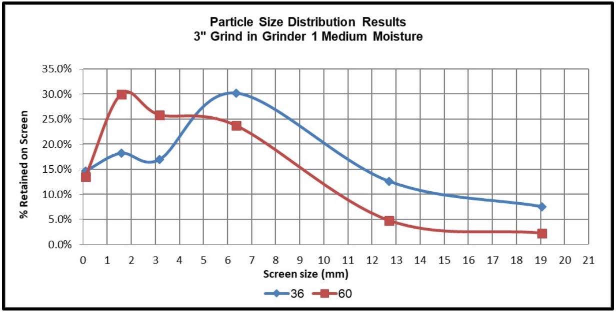
Analysis of the impact of biomass characteristics and equipment setting on particle size distribution after grinding.

- The data is collected from INL's PDU.
- The data is organized based on:
  - Biomass type: Corn stover, switchgrass
  - Moisture level: low, medium, high
  - Grinder mill speed: 36, 41, 51, 60 Hz
  - Infeed rate: 2%, 5%, 10%, 20%, 30%
- We use the Chi-square test to compare the distributions of particle sizes under different problem settings.

DATA ANALYSIS

RESULTS OF CHI-SQUARE TEST:

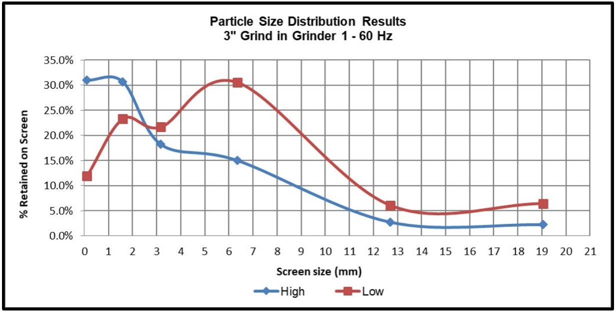
- Increasing the speed of the mill from 36 to 60 Hz, results in smaller particles. The difference in the particle diameter is statistically significant.



DATA ANALYSIS

RESULTS OF CHI-SQUARE TEST:

- Particle diameter of samples with high moisture level is the smallest.
  - The difference in the particle diameter is statistically significant when change in the moisture level is large (i.e. from low moisture to high moisture).



RESULTS & LEARNINGS of DETERMINISTIC MODEL

SCENARIO 1 - NO SYSTEM FAILURE:

Table: Results of the model for a system without machine failure:

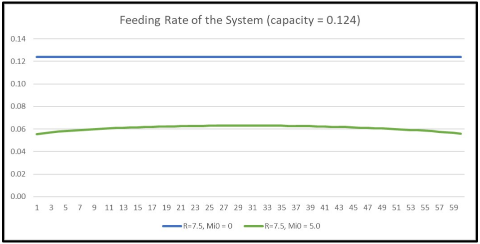
Target Reactor Feeding Rate R (DMT/min)	Metering Bin Capacity (tons)	Starting Inventory at Metering Bin (tons)	Objective Value (tons)	Average Inventory held at Metering Bin (tons)
0.016	5.3	0.0	0.000	0.514
0.083	5.3	0.0	0.000	0.425
0.125	5.3	0.0	0.001	0.000
0.125	5.3	5.0	0.000	3.044

LEARNINGS:

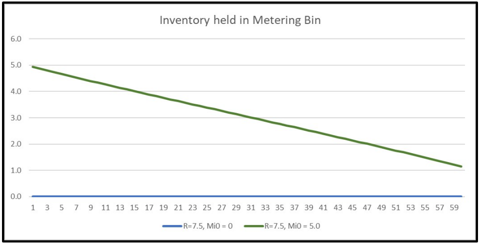
- System's feeding rate becomes a bottleneck.
- System's feeding rate is limited by equipment design.
  - Initial inventory in the metering bin can be used to improve the reliability of the system.

RESULTS & LEARNINGS of DETERMINISTIC MODEL

SCENARIO 1 - NO SYSTEM FAILURE:



- Blue - When target feeding rate R = 7.5, system feeding rate is at its maximum level.
- Green - Maintaining inventory in the metering bin reduces system's feeding rate.



- Blue - No inventory holding.
- Green - Inventory level decreases with time.

RESULTS & LEARNINGS of DETERMINISTIC MODEL

SCENARIO 2 - SINGLE EQUIPMENT FAILURE:

- Screw conveyor 4 is exposed to plugging.
  - Equipment selection is based on experimental results of INL's PDU.
  - Assumption: Failure rate of the equipment is 10%.

Table: Effect of plugging in reliability of the reactor:

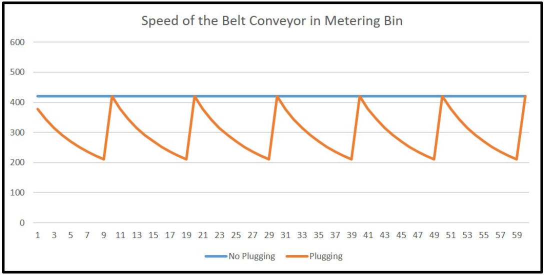
Target Feeding Rate R (DMT/min)	Metering Bin Capacity (tons)	Starting Inventory at Metering Bin (tons)	Objective Value (tons)	Average Inventory held at Metering Bin (tons)	Plugging (Yes / No)
0.125	5.3	0.0	0.001	0.000	No
0.125	5.3	0.0	0.008	0.033	Yes

LEARNINGS:

- Plugging leads to deterioration of reactor's reliability.
  - A realistic modeling of equipment failure is important.

RESULTS & LEARNINGS of DETERMINISTIC MODEL

SCENARIO 2 - SINGLE EQUIPMENT FAILURE:



LEARNINGS:

- The system mitigates the effects of equipment failure.
- Amount and timing of the intervention depends failure rate and distribution.
  - Plugging has a random distribution.
- Deterministic models will not be successful to failure distributions.

FUTURE WORK

DATA ANALYSIS:

- Gather and analyze the following data:
  - Particle size (diameter) distribution prior to grinding.
  - Discharge rate of equipments for different biomass types and settings.

DEM MODELS:

- Finalize DEM models of each equipment
- Integration of DEM model outcomes to the optimization models.

OPTIMIZATION MODELS:

- Conduct a sensitivity analysis of the deterministic model.
  - Use deterministic model as a learning tool for the feeding system.
- Development of stochastic models for reliable and robust systems.

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