DOE Bioenergy Technologies Office (BETO)
2021 Project Peer Review

Integrated Process Optimization for Biochemical Conversion

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March 23, 2021, 12:30 -1:00pm

Project Overview

The **objective of this project** 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 **via developing analytical models**.

POET-DSM paused ethanol production in 2019 [1]

Motivations

Variations in **particle size, high moisture and ash contents** lead to difficulties in handling and feeding biomass to a reactor.

"…*bulk solids handling and material flows through the system*" has been identified as a critical component to achieve the **design throughput of the conversion processes** [3].

Plugged screen in a grinder [2]

Project Overview

I. The DEM model will allow us to:

- Gain an understanding of how biomass properties impact its flowability and size reduction.
- Identify critical design parameters for equipment given biomass properties and processing conditions.

II. The Analytical Model will allow us to:

- Gain an understanding of how biomass properties impact system performance.
- Gain an understanding of how biomass blending impacts system performance.

III. The validation effort at the INL PDU will allow us to:

Demonstrate that in the proposed system, the reactor's **reliability is nearly 90%** for biomass with **10-30% moisture** and **5-15% ash** contents. This testing will be conducted for **60-80 hours**, at a rate of **1 dry tons/hour**.

Quad Chart Overview

Timeline

April 1, 2018
March 30, 2022

	FY 20 Costs	Total Planned Funding (FY 19-Project End Date)
DOE Funded	$956,274	$1,799,998
Project Cost Share*	$147,016	$200,000

Partners

University of Arkansas,
Clemson University,
Idaho National Laboratory,
University of Texas at San Antonio
Matera LLC

Project Goal

Design a system which guarantees process reactor reliability of nearly 90% for infeed biomass with 10-30% moisture and 5-15% ash content.

End of Project Milestone

The proposed process design (developed using analytical models) is validated via experiments at INL's PDU.

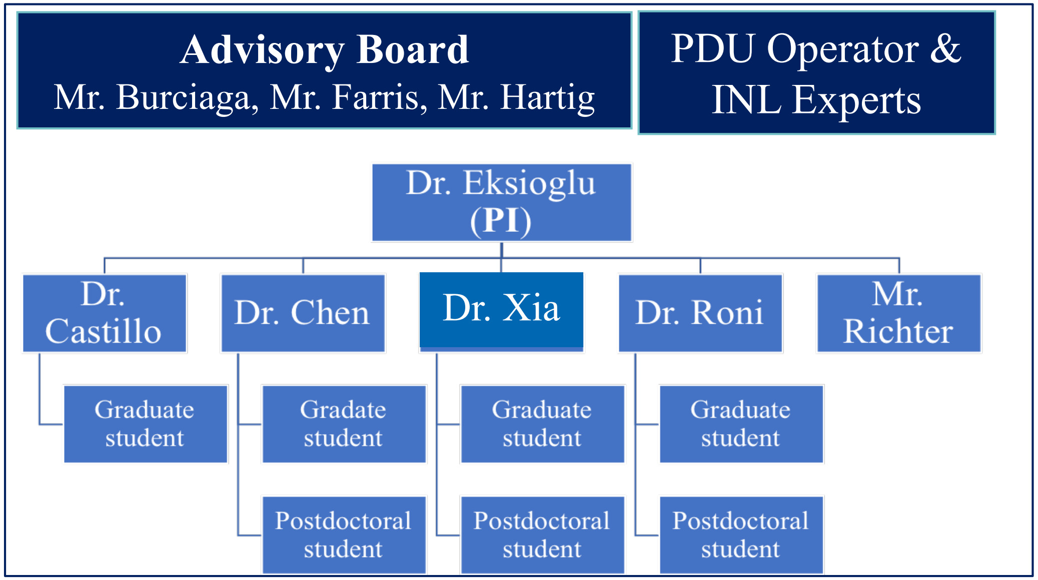
The proposed process design identifies (i) process variables (i.e., system feed rate, screen size); and (ii) buffer location and size, which allows the system to achieve 90% of reactor's design throughput.

Funding Mechanism

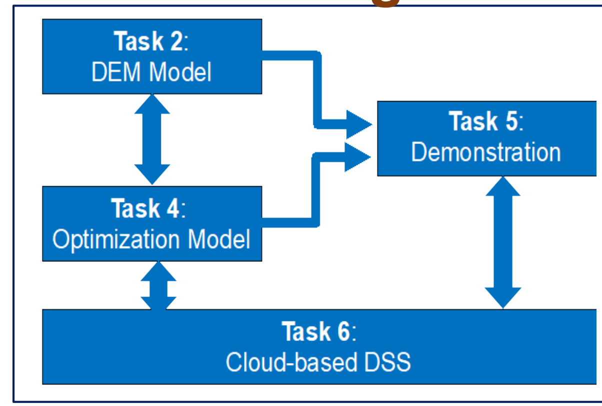
FOA Nr: DE-FOA-0001689
Topic Area: 4

1. Management

Organizational Chart



Process Integration



Responsibilities

Task	% Effort	Leader	Role	Support	Role
1	10	Dr. Eksioglu	Lead the development of website and review of the literature.	Dr. Castillo	Review the literature.
2	20	Dr. Chen	Lead the development and testing of DEM models.	Dr. Huang	Validate/verify DEM models.
3	5	Dr. Eksioglu	Prepare quartely and annual reports. Organize meetings.	Mr. Richter	Coordinate annual meetings.
4	20	Dr. Eksioglu	Lead the development and testing of mathematical models.	Dr. Roni	Validate/verify mathematical models.
5	25	Dr. Roni	Lead the testing the technology at INL's PDU.	Dr. Tumuluru Mr. Yencey	Coordinating the purchase of biomass.
6	15	Dr. Castillo	Lead the developing the decision support system.	All	Validate/verify the DSS.
7	5	Mr. Richter	Establish an assessment team. Conduct market transformation analysis.	Dr. Eksioglu	Coordinate project assessment.

Management Approach

Bi-monthly conference calls/webinars of the team with the Technical Manager, Project Monitor and Advisory Board.
Bi-weekly conference calls/webinars of the team.
Task-specific conference calls and weekly internal meetings with students and faculty.
Visits to INL by university PIs (short-term visits) and by postdocs (work with INL PIs for an extended time)

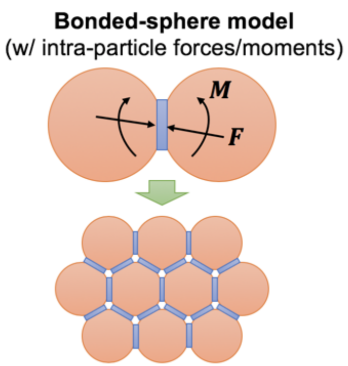
2. APPROACH: DEM

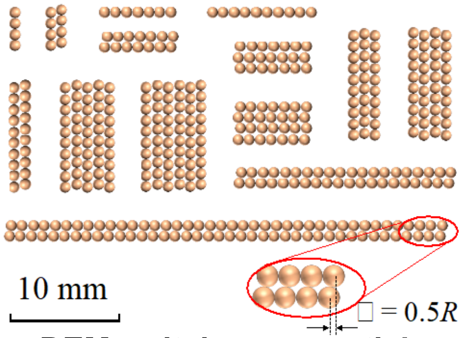
Bonded-sphere discrete element method (DEM)

- Particle mechanics-based numerical method
- Simultaneously capture **complex particle shape**, **a wide range of particle sizes**, and **particle deformability**
- Effective and practical approach capable of simulating both biomass flow and size reduction (lab and equipment scale)

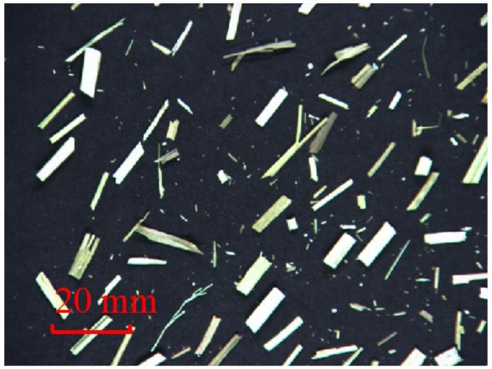
DEM-based regression functions

- Optimization model uses regression functions to link biomass characteristics to behavior
- DEM-based regression functions developed for predicting bulk densities (to quantify flowability) and size reduction as a function of biomass characteristics





DEM switchgrass particles



Switchgrass image analysis

(Guo et al. 2020)

2. APPROACH: DEM

Top challenges faced

- Very limited **physical and mechanical characterization** data
- Complex material behavior (nonlinear, history-dependent, heterogeneous…) & inherent large variations
- DEM is computationally expensive

BP-1 Go/No-Go decision points and metrics

1) Performance of the DEM models to accurately predict biomass material behavior in the proposed process.
   - A systematic and quantitative evaluation of DEM performance against analytical, empirical, and experimental results/data at the particle, lab, and PDU scales. (this addresses some key 2019 Peer review comments on DEM)
2) Usefulness and quality of data at INL
   - Historical data (published and unpublished)
   - New PDU test data (conducted at INL in 2019 and 2020)

We met both criteria and received the "Go" decision after BP-1.

2. APPROACH: Mathematical Models

Process Optimization Model

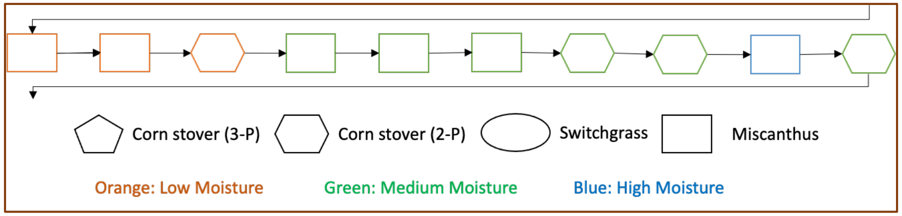
- A **deterministic mixed-integer programming** model
- A **dynamic** model of biomass properties, process variables, and buffer location/size
- **Minimizes processing time** and **maintains reactor utilization** withing 90% of its capacity.
- Evaluates **sequencing** of bales based on moisture level.

Biomass Blending Models

- An **extension** of the Process Optimization model.
- Identifies **blends** of stover, miscanthus and switchgrass to achieve targeted ash and carbohydrate contents for biochemical conversion.

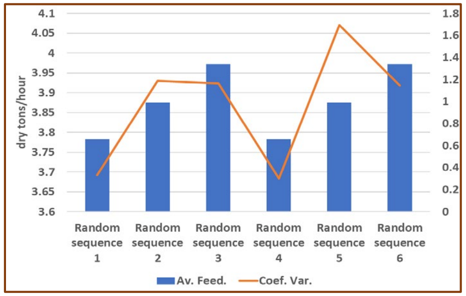
Stochastic Optimization Models

- An **extension** of the Process Optimization model
- Evaluate **stochastic variations** of biomass density, moisture content and particle size on **processing time** and **reactor utilization**.

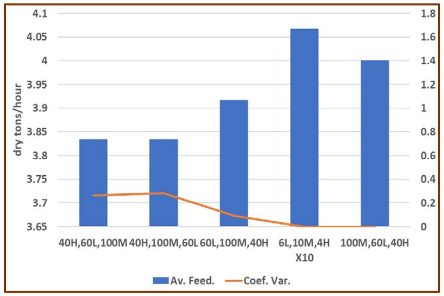


Bale Sequencing

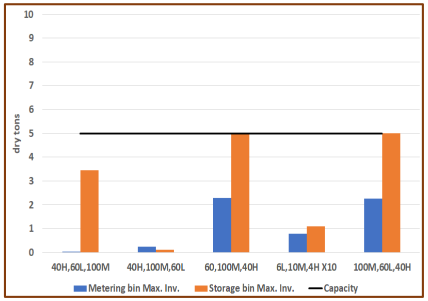
2. APPROACH: Process Optimization



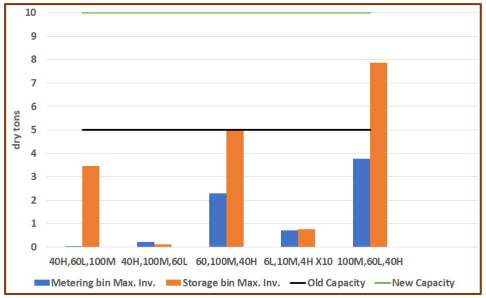
Baseline Control



Proposed Control



No Buffer Capacity Expansions



With Buffer Capacity Expansions

Reactor Feeding and Coefficient of Variation

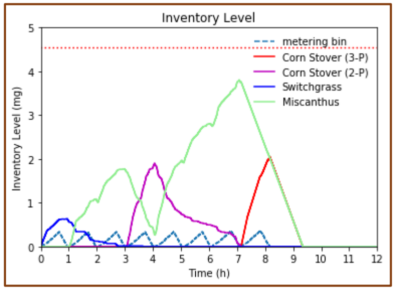
Reactor Target Rate of Proposed Control

OSERVATIONS

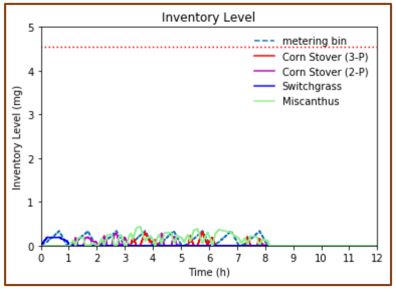
- The proposed control leads up to **7.5% reduction** in the **unit cost** of processing biomass.
- The proposed control leads to approximately **7.5% reduction** of **processing time**.
- **Short feeding patterns L**ow **– Medium – H**igh bales perform the best in terms of costs and processing time.
- There are less variations in feeding of the reactor in the proposed process.

Attribute	Baseline Control	Proposed Control
Control variables	Bale infeed rate, discharge rates from storage units, discharge rate from pelleting	**Buffer size/location**, bale infeed rate, discharge rates from storage units, discharge rate from pelleting
State variables	Amount of processed material in each location during each time step	
Bale sequence	Random	**Bale sequencing** is guided by moisture level and target feed rate to the reactor
Target feed rate to the reactor	Feeding of the system is controlled by product characteristic and target rate of the reactor.	Feeding of the system leads to **maximization of throughput** over the planning horizon.

2. APPROACH: Biomass Blending

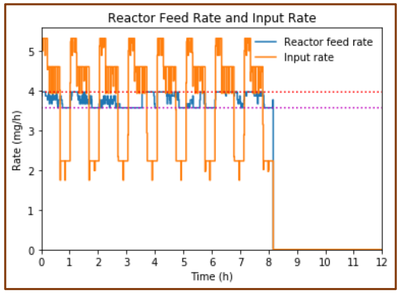


Long Feeding Patterns

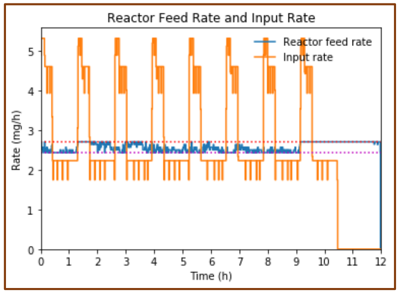


Short Feeding Patterns

Inventory Level



Long Feeding Patterns

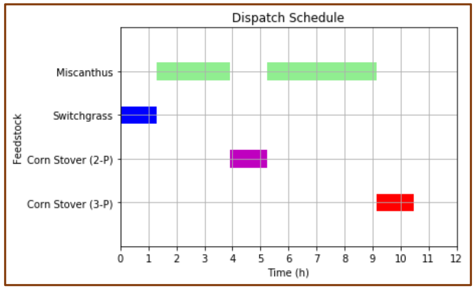


Short Feeding Patterns

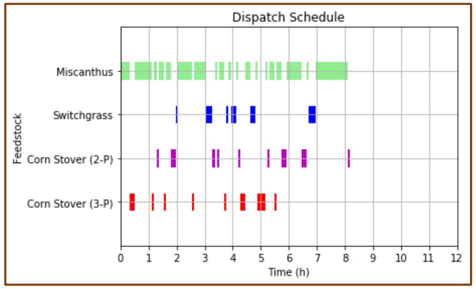
Reactor Feeding Rate

OSERVATIONS

- Processing time of short sequences is **17- 46% shorter** than that of long sequences.
- Processing rate of short sequences is **12- 46% higher** than that of long sequences.
- The maximum inventory level of short sequences is **4 times lower** than that of long sequences.
- Creating a short sequence is labor intensive.



Long Feeding Patterns

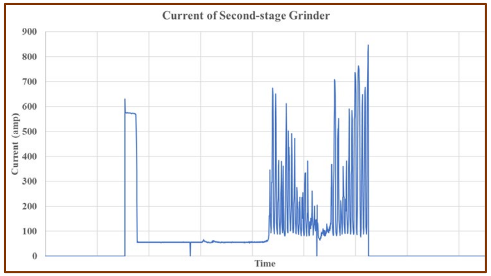


Short Feeding Patterns

Bale Dispatch

2. APPROACH: Challenges Faced

- **Modeling of equipment clogging is challenging because of lack of data.**
  - PDU operator adjusts processing speed of equipment to reduce clogging.
  - No external sources of data are identified.



Power Logger Data

- **Modeling of the relationship among equipment setting, infeed rate, and particle size distribution is challenging because of lack of data.**
  - Extensive experimental data is needed to develop models which describe these relationships.

- **Modeling of the system for miscanthus is challenging because of lack of data.**
  - We do not have historical data from the PDU.
  - Miscanthus is an expensive product, thus, conducting experiments to collect the necessary data is not feasible.

- **The development of the stochastic optimization models is impacted by lack of data necessary to develop distributions of problem parameters.**

3. IMPACT

- **Utilizing** the results of the **analytical models** to guide planning of proposed process control **can lead to**:
  - Reduced process time and costs
  - Reduced impact of feedstock variations on reactor’s uptime
  - Prevent equipment clogging

- The results of this research are **disseminated** via:
  - 2 refereed journal publications
  - 4 manuscripts submitted for publication
  - 2 conference proceedings
  - 8 presentation in professional conferences

3. IMPACT

I. Publications

- Guo, Y., Chen, Q., Xia, Y., Westover, T., Eksioglu, S., & Roni, M. “Discrete element modeling of switchgrass particles under compression and rotational shear”. *Biomass and Bioenergy*, 141, 105649, 2020. https://doi.org/10.1016/j.biombioe.2020.105649 (Tasks 2.2 & 2.3).
- Liu, D., S.D. Ekşioğlu, M. Roni, F. Kucuksayacigil “Optimization Models for Streamlining of Biomass Processing Systems,” Submitted to *Proceedings of the Institute of Industrial and Systems Engineers Annual Conference* (May 2021) (Tasks 4.3 & 4.4).
- Kucuksayacigil, F., S.D. Eksioglu, M. Roni, Q. Chen, K. Castillo “A reliable biomass process design in an integrated biorefinery,” *Proceedings of the Institute of Industrial and Systems Engineers Annual Conference* (Nov. 2020) (Tasks 4.2 & 4.4).
- Kucuksayacigil, F., M. Roni, S.D. Eksioglu, “Optimal Control of Feedstock Preprocessing to Handle Variations in Feedstock Characteristics and Reactor In-Feed Rate,” Submitted to *International Journal of Energy*, 2020 (Task 4.2 & 4.4).
- Gulcan, B., S.D. Eksioglu, Y. Song, M.D. Roni “Optimization Model for Integrated Biorefinery Operations,” Submitted to *Optimization Letters*, 2021 (Tasks 4.2 & 4.4).
- Xia, Y., Z. Lai, T. Westover, J. Klinger, H. Huang and Q. Chen, “Discrete element modeling of deformable pinewood chips in cyclic loading test”, *Powder Technology*, 345: 1-14, https://doi.org/10.1016/j.powtec.2018.12.072, 2019. (Task 2.2)
- Guo, Y., Chen, Q., Xia, Y., Klinger, J., & Thompson, V. “A nonlinear elasto-plastic bond model for the discrete element modeling of woody biomass particles”, *Powder Technology*, in revision, 2021. (Task 2.2)
- Lai, Z., Y. Xia, H. Huang, T. Westover and Q. Chen, “Discrete element modeling of granular hopper flow of irregular-shaped deformable particles”, in review, 2019. (Tasks 2.2 & 2.3)

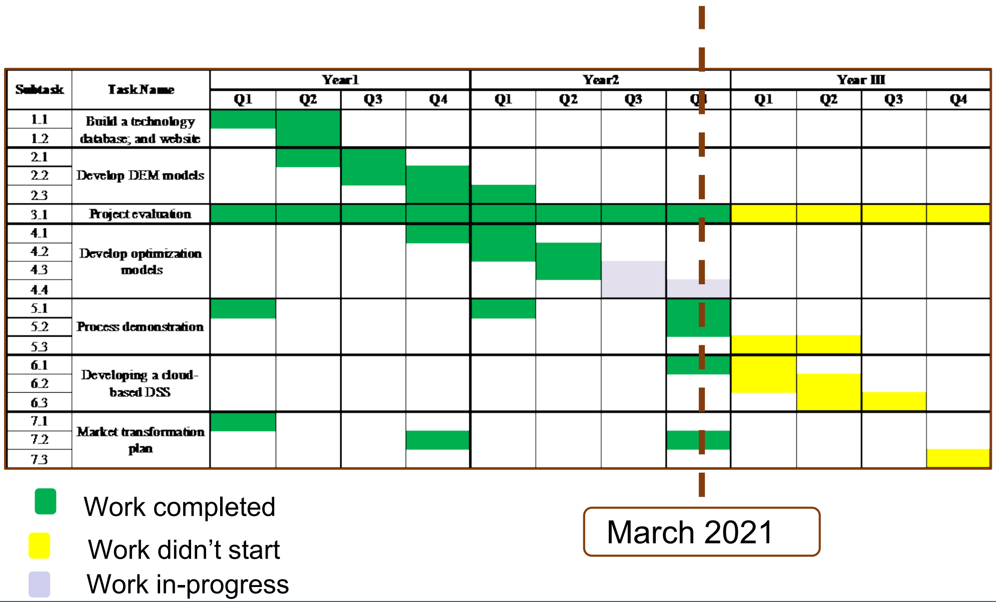
3. IMPACT

II. Presentations

- Gulcan, B., S.D. Eksioglu, Y. Song, M. Roni, Q. Chen "Optimization models for integrated biorefinery operations," *Virtual Annual Meeting of INFORMS*, November 2020 (Tasks 4.2 & 4.4).
- Kucuksayacigil, F., M. Roni, S.D. Eksioglu, Q. Chen, K. Castillo "Optimization of biomass process design in an integrated biorefinery," *Virtual Annual Meeting of INFORMS*, November 2020 (Tasks 4.2 & 4.4).
- Kucuksayacigil, F., S.D. Eksioglu, M. Roni, Q. Chen, K. Castillo "A reliable biomass process design in an integrated biorefinery," *Virtual IISE Annual Conference*, November 2020 (Tasks 4.2 & 4.4).
- Chen, Q., Guo, Y., Tasnim, Z., Xia, Y., Roni, M., & Eksioglu, S. "Discrete element modeling of switchgrass particles for integrated process optimization". *Virtual AIChE 2020 Annual Meeting*, November 2020 (Tasks 2.2 & 2.3).
- B. Gulcan, S.D. Eksioglu, M. Roni, K. Castillo, "Integrated Process Optimization for Biochemical Conversion," *IISE Annual Meeting*, Orlando, FL (2019). (Task 4.1)
- Y. Guo, Q. Chen, Y. Xia, M. Roni and S. Eksioglu, "Discrete element modeling of chopped switchgrass: particle size and shape effects on bulk mechanical properties", *Engineering Mechanics Institute and Geo-Institute Specialty Conference*, Pasadena, CA, (2019). (Tasks 2.2 & 2.3)
- Y. Xia, Z. Lai, Q. Chen, T. Westover, J. Klinger and H. Huang, "Discrete element modeling of granular flow of flexible woody biomass particles", *Engineering Mechanics Institute and Geo-Institute Specialty Conference*, Pasadena, CA, (2019). (Tasks 2.2 & 2.3)
- Z. Lai, Y. Xia, H. Huang, T. Westover and Q. Chen, "Numerical characterization of biomass flowability in biorefinery", *Idaho National Laboratory Annual Intern Expo,* Idaho Falls, ID, (2018). (Task 2.2)

4. PROJECT OUTCOMES

- BP 1 tasks are completed.
- BP 1 Go-No-Go is completed.
- BP 2 work will be completed by May 15^{th}.
- We are in the process of scheduling our BP 2 Go-No-Go.



4. PROJECT OUTCOMES: DEM

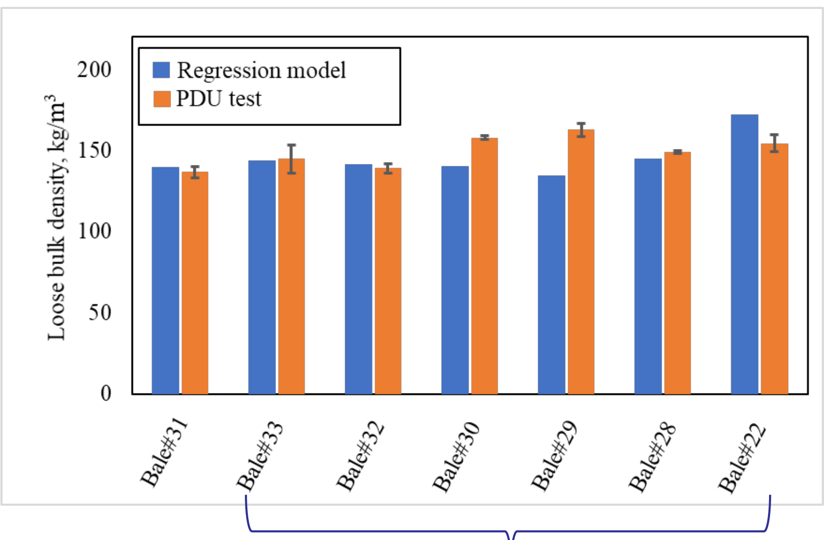
Technical accomplishments (DEM)

- A bonded-sphere DEM model developed and validated specifically for switchgrass (published in Biomass & Bioenergy: Guo et al. 2019)
- DEM-based regression functions for predicting bulk densities (used to quantify flowability) as a function of biomass particle sizes and moisture contents, and functions validated with PDU data.

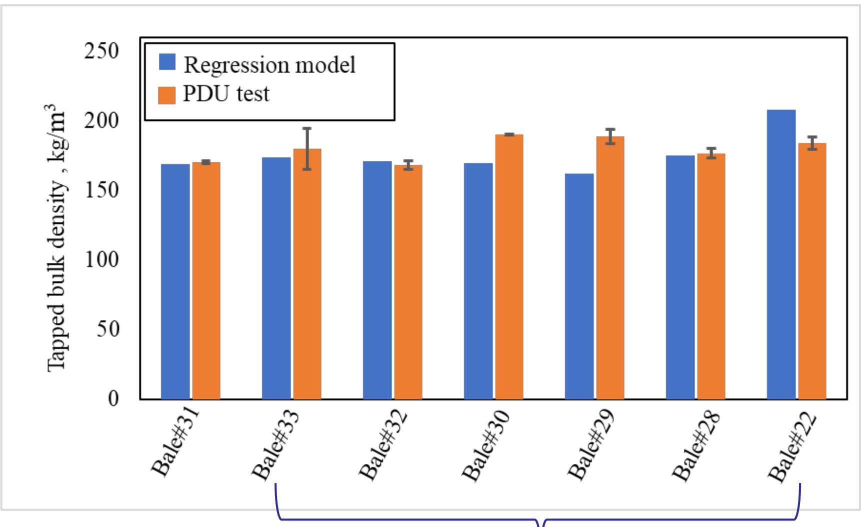
Functions for predicting loose and tapped bulk densities

$$\rho_{loose} = 186.348 + 206.1697\omega - 110.302\, D_{50} + 0.709\, \frac{D_{90}}{D_{10}}$$

$$\rho_{tapped} = 224.755 + 248.661\, \omega - 133.036\, D_{50} + 0.856\, \frac{D_{90}}{D_{10}}$$



Prediction sets



Prediction sets

4. PROJECT OUTCOMES: Math Model

Technical accomplishments (Math Model)

- A deterministic model is developed to evaluate the impact of buffer size and location, and moisture level on processing time and reactor's utilization of switchgrass (submitted to *International Journal of Energy*: Kucuksayacigil et al. 2020).

- A biomass blending model is developed to evaluate the impact of biomass characteristics (ash and carbohydrate contents) on processing time and reactor's utilization of switchgrass (submitted to *Proceedings of IISE Annual Conference*: Liu et al. 2021).

- A stochastic model to evaluate the impact of biomass moisture level and particle size distribution on processing time and reactor utilization using data about switchgrass (submitted to Optimization Letters: Gulcan et al. 2021.)

5. PROJECT SUMMARY

I. The DEM models show:

- Bonded-sphere DEM developed and validated that capture key biomass particle characteristics
- DEM-based functional relationships capable of predicting biomass flowability (quantified using bulk density) as a function of biomass characteristics; validation using PDU data showed the accuracy met the criteria set in Go/No-Go.
- DEM grinding models account for physics of particle breakage and could predict the entire output particle size distribution.

II. The analytical models show:

- The proposed system control leads up to **7.5% reduction** in the unit cost and processing time of biomass as compared to basic control.
- Using **short sequences of bales**, created based on moisture level, leads to reductions of processing time and cost while maintaining a continuous flow of biomass to the reactor.
- Blending of biomass allows the system to meet process requirements at all time.

REFERENCES

[1] http://ethanolproducer.com/articles/15344/zero-to-10-million-in-5-years.

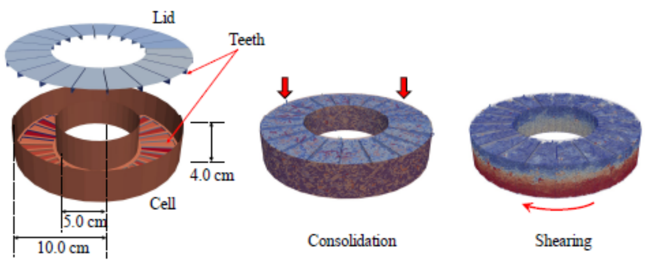
[2] Neal Yancey and Jaya Shankar Tumuluru, Idaho National Laboratory.

[3] DOE (2016). "*Biorefinery Optimization Workshop Summary Report*". Chicago, Illinois, U.S. Department of Energy.

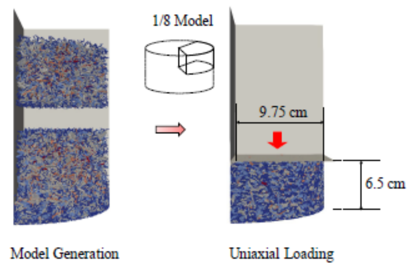
Additional Slides DEM

APPROACH: DEM

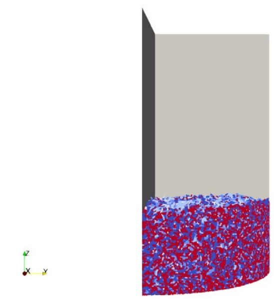
- DEM calibration using INL mechanical test data of switchgrass



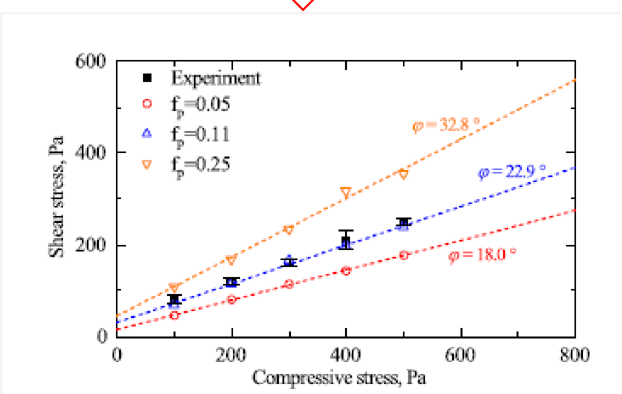
Ring shear test



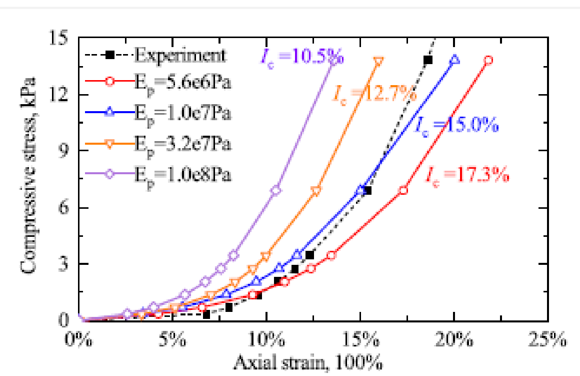
Compression test



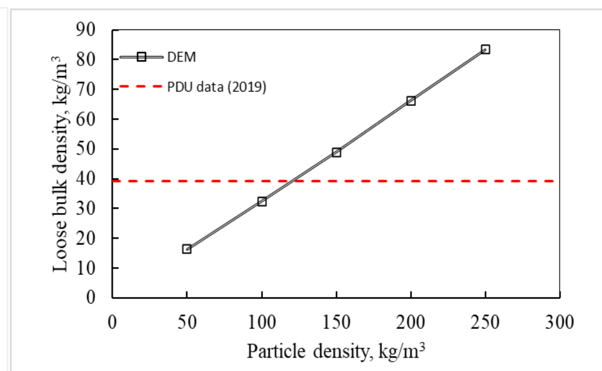
Bulk density test



Particle friction calibration



Young's modulus calibration



Particle density calibration

DEM-based regression models

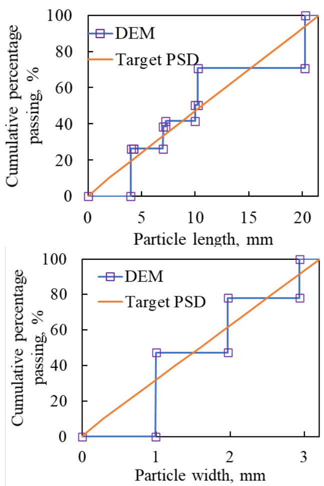
- Bulk Density prediction (after Grinder -1):

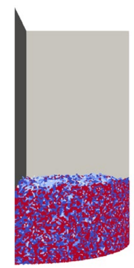
Generating particle size distribution for DEM

DEM simulation (30 cases) and regression of ρ_{loose} & ρ_{tapped}

Obtaining wet ρ_{loose} & ρ_{tapped} using $\rho_{wet} = \frac{\rho_{dry}}{1-\omega}$

Parameter	D_{50}, mm	D_{90}/D_{10}
Ranges from PDU (2019)	1.77 – 2.31	1.6 – 2.6
Values used in DEM	10.23 – 14.85	8 - 16





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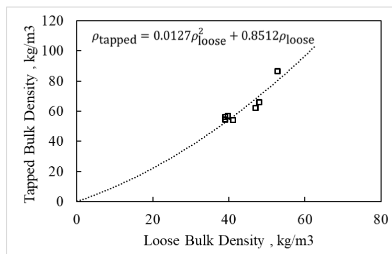
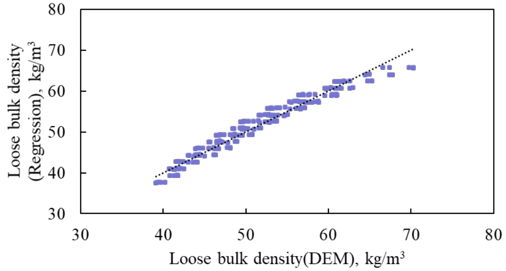
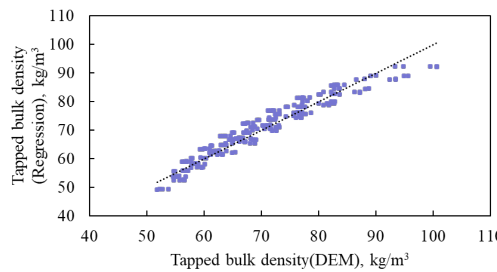


210 data points

$$\rho_{loose} = 56.183 + 65.312\omega - 8.473D_{50} + 0.015\frac{D_{90}}{D_{10}}$$



$$\rho_{tapped} = 86.334 + 89.441\omega - 16.087D_{50} + 0.022\frac{D_{90}}{D_{10}}$$



Infer ranges from PDU test data (2019)

Fitting particle length and width

Obtaining dry ρ_{loose} & ρ_{tapped} values

Regression models

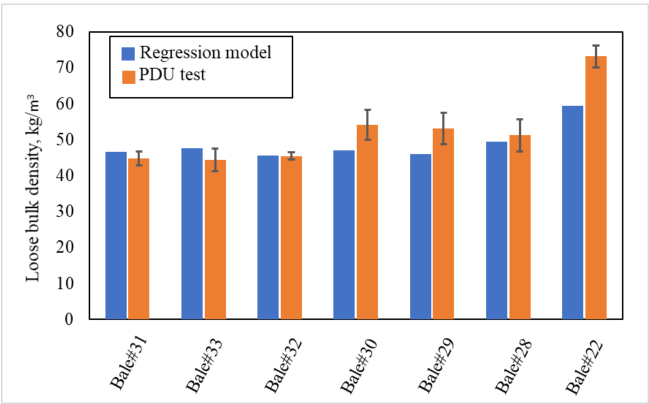
*Regression model predicts wet ρ_{loose} & ρ_{tapped} values.
*Same methodology is followed for prediction of ρ_{loose} & ρ_{tapped} after Grinder -2

Validation of DEM mdoel with PDU test

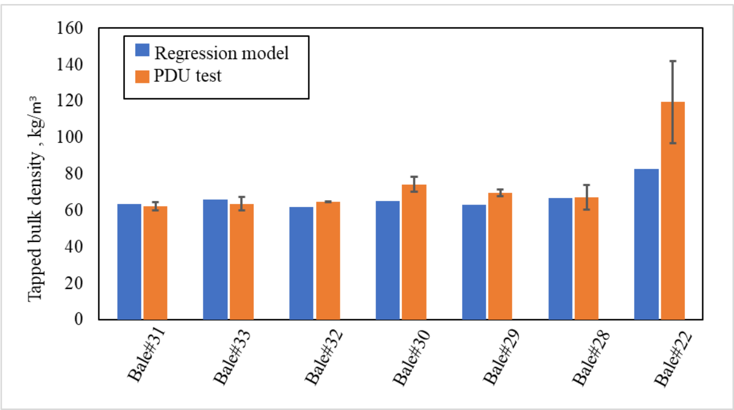
- Validation of DEM regression model :

After Grinder -1 :

$$\rho_{loose} = 56.183 + 65.312\omega - 8.473D_{50} + 0.015\frac{D_{90}}{D_{10}}$$

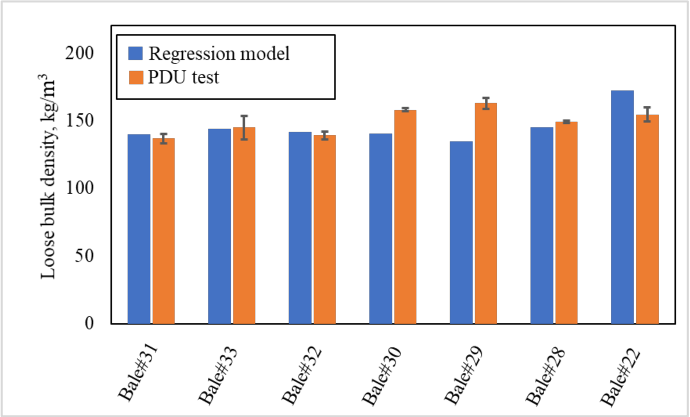


$$\rho_{tapped} = 86.334 + 89.441\omega - 16.087D_{50} + 0.022\frac{D_{90}}{D_{10}}$$

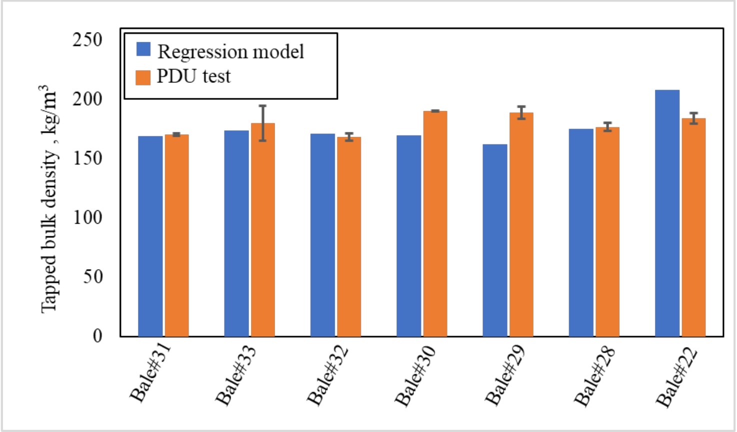


After Grinder -2 :

$$\rho_{loose} = 186.348 + 206.1697\omega - 110.302\ D_{50} + 0.709\ \frac{D_{90}}{D_{10}}$$



$$\rho_{tapped} = 224.755 + 248.661\ \omega - 133.036\ D_{50} + 0.856\ \frac{D_{90}}{D_{10}}$$



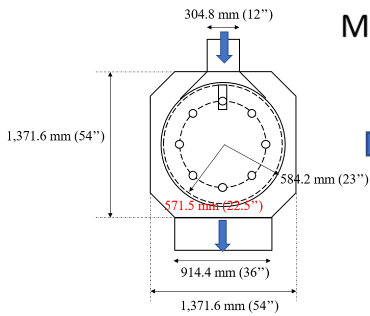
DEM grinding model

- Grinder -2 model

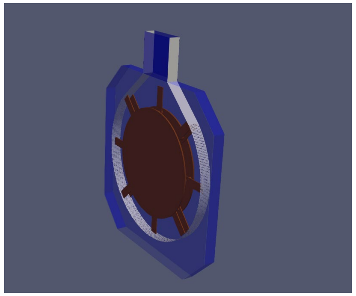
CAD drawings

Meshing

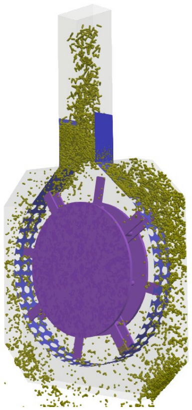
G-2 PDU equipment



G-2 PDU measurements

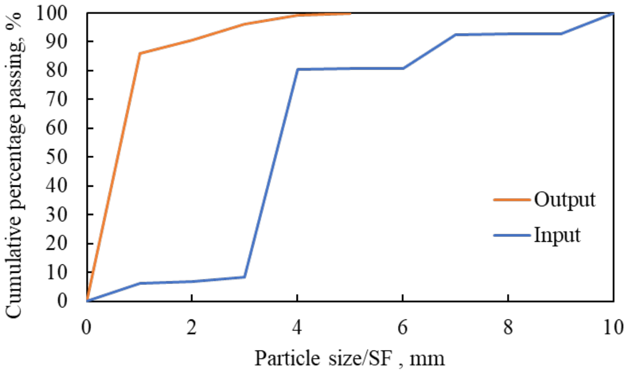


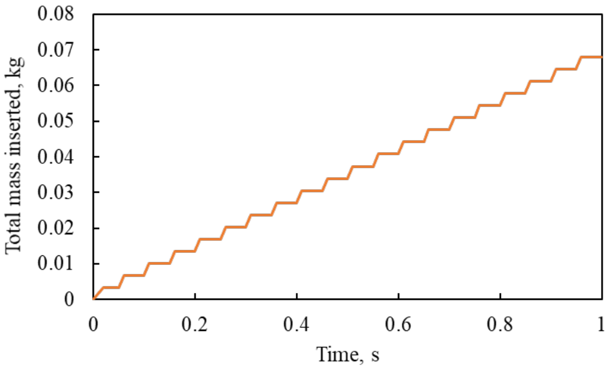
STL files



G-2 model

- Scaling law applied
- Same particle rate
- Same screen opening to particle size ratio
- Particle templates : 4 , 7, 10 mm
- Without pan and increased domain cases





Particle size distribution and size parameters match quite well with SF = 4

Additional Slides Math Model

2. APPROACH: Mathematical Model

Control Variables:

Z_t: Infeed rate of the system at period t (*dry tons*)

X_{it}: Outflow from equipment i at period t (*dry tons*)

M_{it}: Inventory level in equipment i at period t (*dry tons*)

V_{it}: Speed of the conveyor belt at period t (m)

Problem Parameters:

w, *h* : height (*m*) and width (*m*) of a bale

d : density of a bale (*dry tons/m³*)

γ_{it} : amount of biomass per *m* of conveyor belt

e.g., $\gamma_{1t} = w \times h \times d$ (*tons/m*)

U_i: Processing capacity of equipment *i* (*dry tons*)

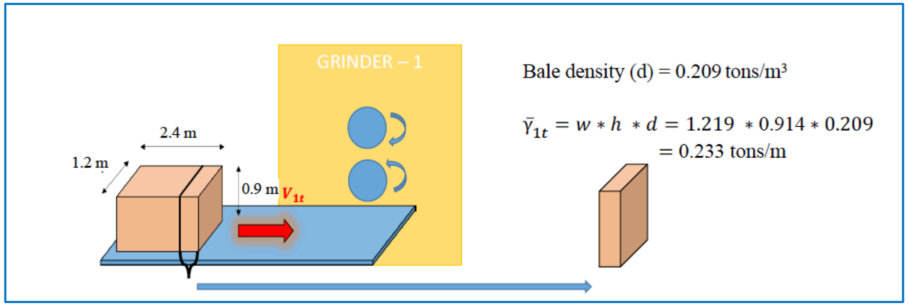
I: Set of equipment in the facility

Model Constraints:

A. Operational constraints ($\forall\, t \in T$):

$$Z_t \leq \gamma_{1t} V_{1t}.$$

The amount of biomass fed to the system depends on the speed of conveyor belt (V_{1t}) and biomass characteristics (*d*).



B. Capacity constraints ($\forall\, i \in I, t \in T$):

$$X_{it} \leq U_i,$$
$$M_{it} \leq U_i.$$

The amount of biomass processed and inventoried is limited by processing/storage capacity of equipment.

2. APPROACH: Mathematical Model

Model Constraints:

C. Inventory balance constraints ($\forall\ i \in I, t \ \in T$):

$$M_{it} = M_{it-1} + X_{i-1t} - X_{it}.$$

Storage: The amount of inventory in the current period depends on the inventory from the previous period, the flow in, and the flow from the equipment in the current period.

D. Flow balance constraints ($\forall\ i \in I, t \ \in T$):

$$X_{it} = X_{i-1,t}.$$

Conveyors: The amount of flow from a conveyor equal the amount to this conveyor.

E. Reliability constraints ($\forall\ t \ \in T$):

$$X_{rt} \leq U_r,$$
$$X_{rt} \geq L_r,$$
$$1/_T \sum_{t=1}^{T} X_{rt} = R.$$

Reactor:
r – index representing the reactor
Ur – processing capacity
Lr – lower bound
R - targeted processing rate

F. Non-negativity and integer constraints.

Objective:

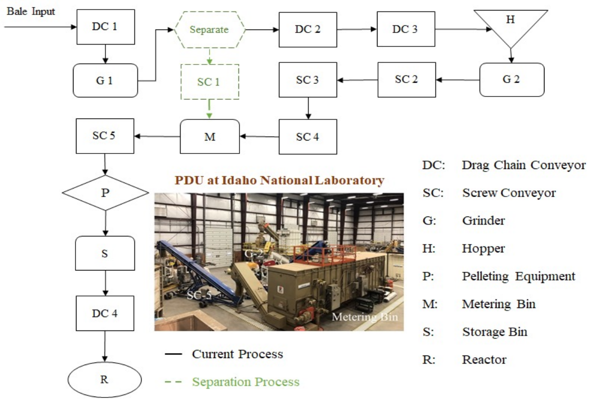
Minimize system wide costs

Notice:

- Energy costs are in $/hour:
  By minimizing energy costs, we are also minimizing processing time
- Storage costs:
  Inventory holding costs and amortization cost of new storage equipment

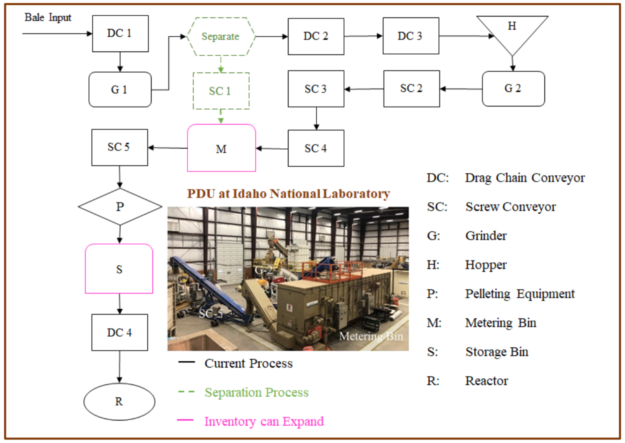
2. APPROACH: Experimental Setup

Baseline Control



Capacities of storage units ***are not*** *expanded*

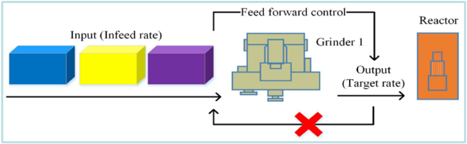
Proposed Control



Capacities of storage units ***can be*** *expanded*

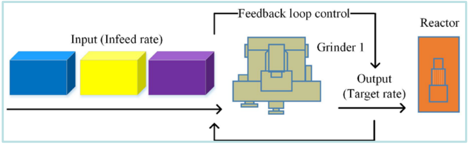
Attribute	Baseline Control	Proposed Control
Control variables	Bale infeed rate, discharge rates from storage units, discharge rate from pelleting	**Buffer size/location**, bale infeed rate, discharge rates from storage units, discharge rate from pelleting
State variables	Amount of processed material in each location during each time step	
Bale sequence	Random	**Bale sequencing** is guided by moisture level and target feed rate to the reactor
Target feed rate to the reactor	Feeding of the system is controlled by product characteristic and target rate of the reactor.	Feeding of the system leads to **maximization of throughput** over the planning horizon.

Baseline Control



Infeed of system ***is not*** *driven by the feeding of reactor.*

Proposed Control



Infeed of system ***is*** *driven by the feeding of the reactor.*

2. APPROACH: Data Collection

Data Sources

- Focused experiments conducted at PDU in 2019 and 2020: switchgrass
- Historical data at PDU: switchgrass
- Discussions with operators of PDU

Case scenario Bale moisture entering into pre-processing		High 25%	Medium 17.5%	Low 10%
Stage-1 Size Reduction				
Operating conditions	Dry bulk density (lb/cubic feet)	9	9	9
	Moisture	25.0%	17.5%	10.0%
Process performance	Moisture loss	4.77%	3.00%	0.50%
	Dry matter loss	1.50%	1.50%	1.50%
	Bulk density change (lb/cubic feet)	-5.70	-6.43	-6.56
	D50 (mm)	1.77	2.31	1.94
	D90 (mm)	4.61	7.23	5.90
	D10 (mm)	0.45	0.59	0.47
	Maximum in-feed rate (dry tons/hour)	2.42	4.99	5.77
Separations				
Operating conditions	Moisture	20.23%	14.50%	9.50%
	Bulk density (lb/cubic feet)	3.30	2.57	2.44
Process performance	Bypass	40.48%	44.98%	49.98%
	Moisture loss	0.71%	0.51%	0.00%

Case scenario Bale moisture entering into pre-processing		High 25%	Medium 17.5%	Low 10%
Stage-2 Size Reduction				
Operating conditions	Moisture	19.5%	14.0%	9.50%
Process performance	Moisture loss	4.0%	3.0%	0.70%
	Dry matter loss	0.5%	0.5%	0.5%
	Bulk density change (lb/cubic feet)	4.14	5.13	5.61
	D50 (mm)	0.61	0.66	0.63
	D90 (mm)	1.49	1.47	1.43
	D10 (mm)	0.17	0.23	0.22
	Maximum in-feed rate (dry tons/hour)	1.75	3.09	5.76
Densification				
Operating conditions	Moisture	15.5%	11.0%	8.80%
	Bulk density (lb/cubic feet)	7.44	7.70	8.05
Process performance	Moisture loss	3.9%	1.50%	0.00%
	Bulk density change (lb/cubic feet)	34.12	33.86	33.51
	Maximum in-feed rate (dry tons/hour)	3.68	4.20	5.25
Pellet Property				
	Dry bulk density (lb/cubic feet)	41.56	41.56	41.56
	Durability	97.60%	97.60%	0.98
	Moisture	10.7%	9.0%	8.80%

2. APPROACH: Experimental Setup

Product Characteristics:

- ❑ 200 bales of switchgrass
- ❑ 60 bales have low (L) moisture content
- ❑ 100 bales have medium (M) moisture content
- ❑ 40 bales have high (H) moisture content

Control strategies	Biomass Feeding Patterns
Baseline control	Random sequences 1,…, 6
Proposed control	60L,100M,40H in this order
	100M,60L,40H in this order
	40H,60L,100M in this order
	40H,100M,60L in this order
	6L,10M,4H X10 in this order

Performance Metrics:

- ❑ Average feeding of reactor (Av. Feed.)
- ❑ Average inventory over planning horizon (Av. Inv.)
- ❑ Cost of operating the system ($/dry ton)
- ❑ Maximum inventory over planning horizon (Max. Inv.)
- ❑ Processing time (minutes)
- ❑ Variability in feeding of the reactor (Coef. Var.)

2. APPROACH: Numerical Results

Job (bale) sequencing and inventory holding are strategies used in practice to streamline processes.

Proposed control versus **baseline control** model.

Control strategies	Feeding patterns	Unit Cost ($/dry ton)	Processing Time (hours)	Av. Inv. (dry tons)	Max. Inv. (dry tons)	Av. Feed. (dry tons/hour)	Coef. Var.
Baseline control	Random sequence 1	33.88	22.40	0.32	1.61	3.78	0.33
	Random sequence 2	33.08	21.87	0.54	2.93	3.87	1.19
	Random sequence 3	32.28	21.33	0.60	2.82	3.97	1.16
	Random sequence 4	33.88	22.40	0.41	2.42	3.78	0.30
	Random sequence 5	33.08	21.87	3.72	5.94	3.87	**1.69**
	Random sequence 6	32.28	21.33	0.69	2.87	3.97	1.14
Proposed control	60L,100M,40H	32.73	21.63	4.56	7.29	3.92	0.09
	100M,60L,40H X 1	**33.87**	**21.18**	**5.12**	**11.63**	4.00	0.00
	40H,60L,100M **X 1**	33.43	22.10	1.17	3.46	3.83	0.26
	40H,100M,60L **X 1**	33.43	22.10	0.03	0.34	3.83	0.28
	6L, 10M, 4H X10	**31.53**	**20.83**	0.69	1.47	**4.07**	0.00

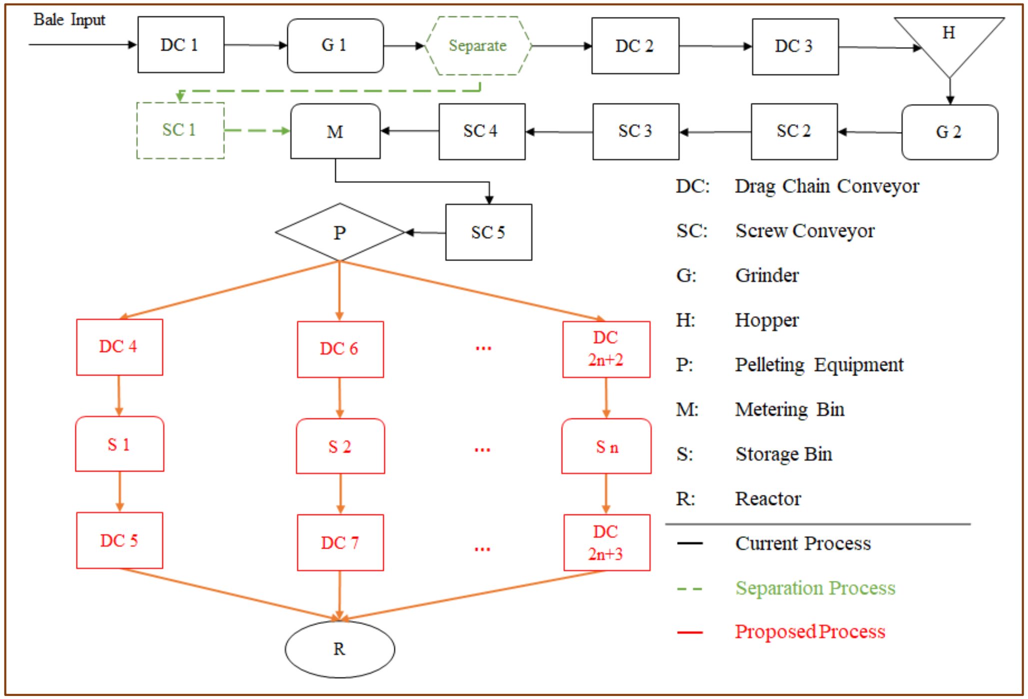
OSERVATIONS

- The proposed control leads up to **7.5% reduction** in the unit cost of processing biomass.
- The proposed control leads to approximately **7.5% reduction** of processing time.
- **Short feeding patterns L – M – H** perform the best in terms of costs and processing time.
- There are less variations in feeding of the reactor in the proposed process.

2. APPROACH: Biomass Blending Model

ASSUMPTIONS

- One biomass feedstock is processed at a time; thus, each pellet is made of a single feedstock.
- Pellets are stored in dedicated storage areas.
- In each time period, the blend of pellets (from different feedstocks) fed to the reactor meets ash and carbohydrate content requirements.



The Proposed Process Design of PDU

2. APPROACH: Experimental Setup

Biochemical Conversion Process: Target Rates

Ash Content	Carbohydrate Content
7.4 %	59.1 %

Biomass Characteristics

Biomass Feedstock	Ash Content (%)	Carbohydrate Content (%)
Corn stover (3-P)	12.2	57.4
Corn stover (2-P)	7.6	60.3
Switchgrass	6.4	66.6
Miscanthus	2.5	81.7

Composition of Bales Based on Moisture Level

Low	Medium	High
30%	50%	20%
50%	30%	20%
20%	30%	50%

60 Bales

Distribution of Nr. Of Bales

Biomass Feedstock	Moisture Level		
	Low	Medium	High
Corn stover (3-P)	3	5	2
Corn stover (2-P)	3	5	2
Switchgrass	3	5	2
Miscanthus	15	25	10

2. APPROACH: Experimental Setup

<table>
<tr><th rowspan="2">Problem Nr</th><th colspan="2">Sequencing Based on</th><th rowspan="2">Problem Nr</th><th colspan="2">Sequencing Based on</th></tr>
<tr><th>Moisture</th><th>Feedstock</th><th>Moisture</th><th>Feedstock</th></tr>
<tr><td>1</td><td>3L 5M 2H</td><td rowspan="8">10S 20M 10C2 30M 10C3</td><td>10</td><td rowspan="5">3L 5M 2H</td><td>50M 10S 10C2 10C3</td></tr>
<tr><td>2</td><td>3L 2H 5M</td><td>11</td><td>10S 50M 10C2 10C3</td></tr>
<tr><td>3</td><td>5M 2H 3L</td><td>12</td><td>10M 10C3 20M 10C2 20M 10S</td></tr>
<tr><td>4</td><td>5M 3L 2H</td><td>13</td><td>Sequence *</td></tr>
<tr><td>5</td><td>2H 3L 5M</td><td>14</td><td>Sequence **</td></tr>
<tr><td>6</td><td>2H 5M 3L</td><td>15</td><td>L</td><td rowspan="3">Sequence **</td></tr>
<tr><td>7</td><td>5L 3M 2H</td><td>16</td><td>M</td></tr>
<tr><td>8</td><td>2L 3M 5H</td><td>17</td><td>H</td></tr>
<tr><td>9</td><td>H</td><td>50M 10S 10C2 10C3</td><td>18</td><td>Random</td><td>Random</td></tr>
</table>

Moisture Sequence
L – low moisture
M – medium moisture
H – high moisture

Feedstock Sequence
M – miscanthus
S – switchgrass
C2 – stover 2 pass
C3 – stover 3 pass

Sequence*

10S-(2M-1C2-3M-2C2-1M-1C2)-(2M-1C2-3M-2C2-1M-1C2)-(2M-1C3-3M-2C3-1M-1C3)
(2M-1C2-4M-1C2-2M)-(2M-1C3-3M-2C3-1M-1C3)-10M-(2M-1C3-4M-1C3-2M)

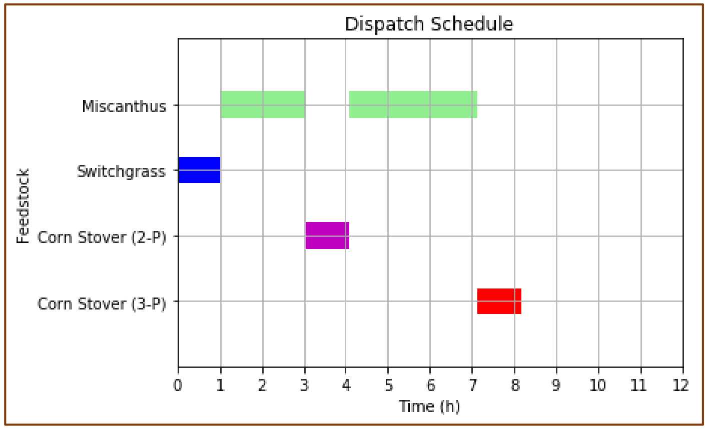
Sequence**

10S-(2M-1C2-3M-2C2-1M-1C2)-(2M-1C2-3M-2C2-1M-1C2)- (2M-1C2-4M-1C2-2M)
(2M-1C3-3M-2C3-1M-1C3)-10M-(2M-1C3-3M-2C3-1M-1C3)-(2M-1C3-4M-1C3-2M)

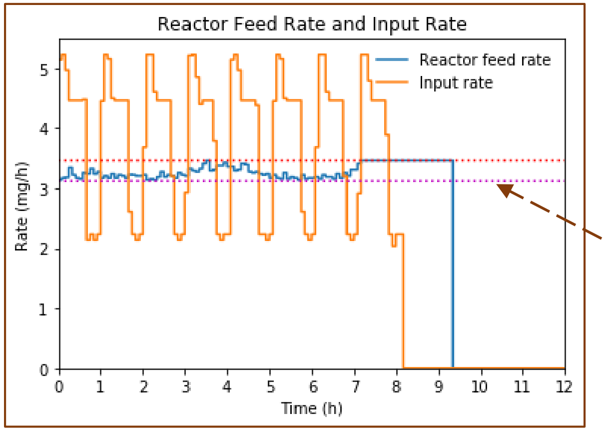
2. APPROACH: Numerical Results

PROBLEM 1

Moisture Level: 3L 5M 2H and Feedstock: 10S 20M 10C2 30M 10C3



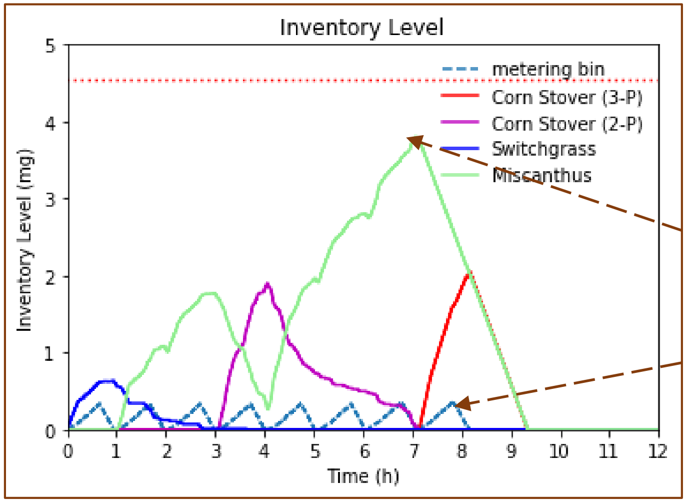
Dispatching of Bales



Processing rate is 3.35 mg/hr.

Reactor's reliability is 90%.

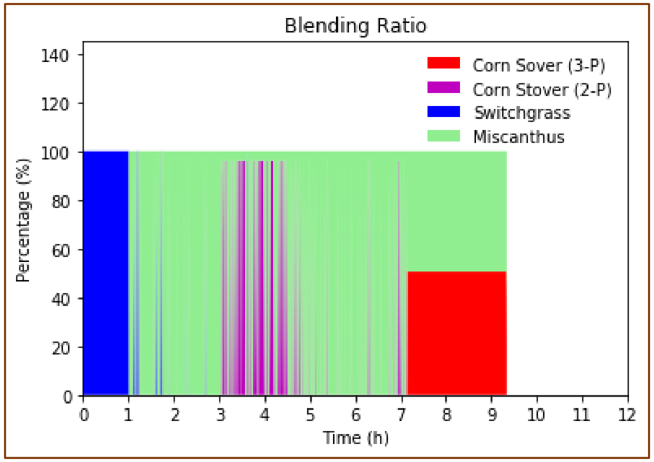
Feeding of the Reactor



Max Inv. of Miscanthus is 3.9mg

Max Inv. of metering bin is 0.4mg

Inventory Level

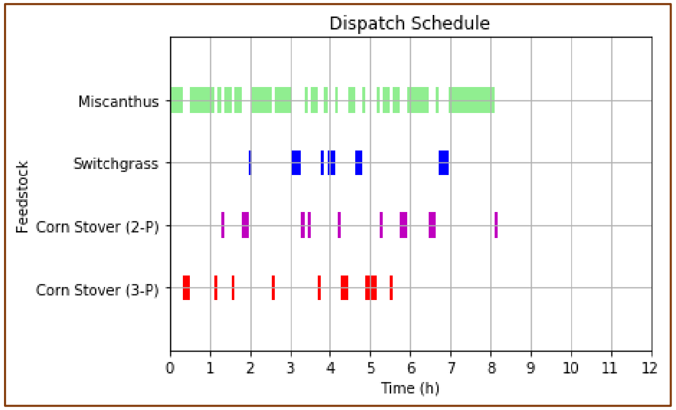


Blended Biomass Feeding the Reactor

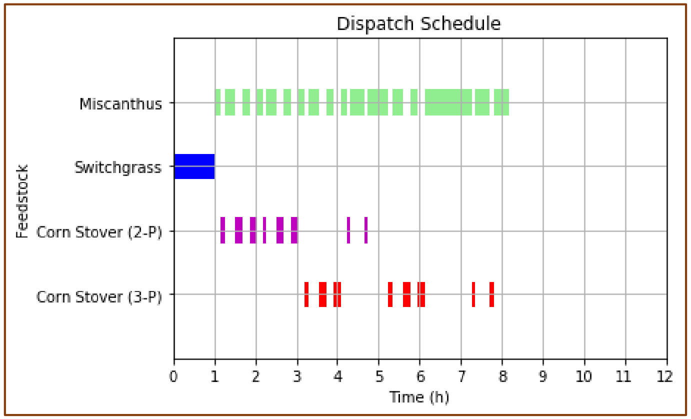
2. APPROACH: Numerical Results

DISPATCHING OF BALES

Processing bale from the same shipment or the same supplier creates a "**long**" sequence.



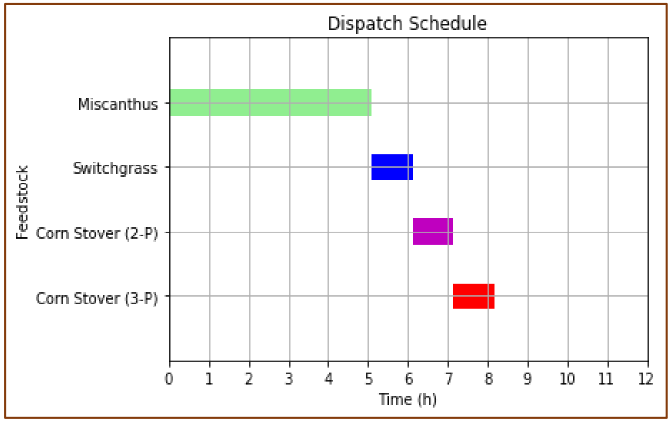
Random Sequence



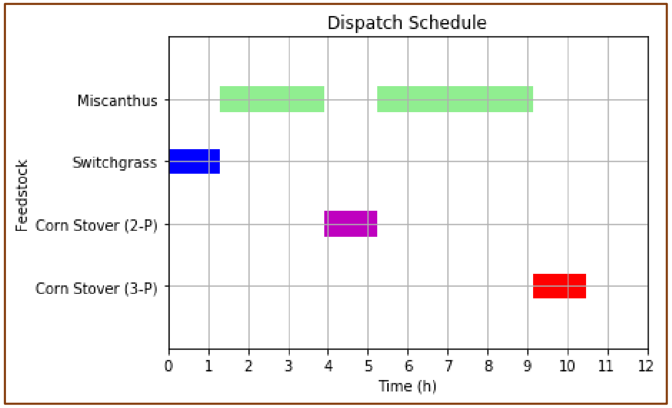
Short Sequence (P 13)

Bale dispatching based on a pre-determined "**short**" sequence is labor expensive.

A "**Random**" sequence dispatches bales from different shipments. No particular order is followed.



Long Sequence (P 10)



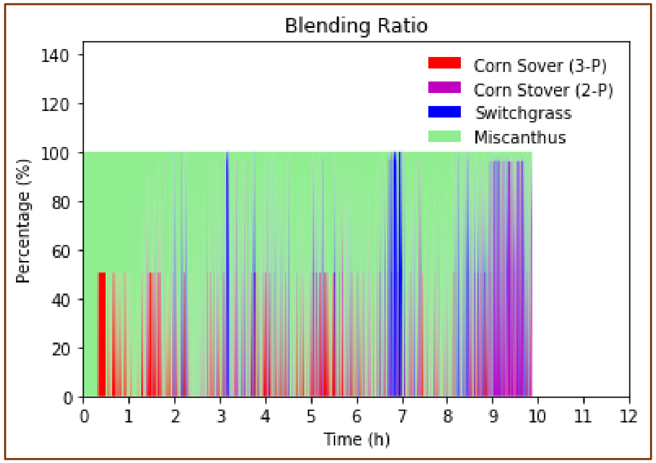
Long Sequence (P 8)

2. APPROACH: Numerical Results

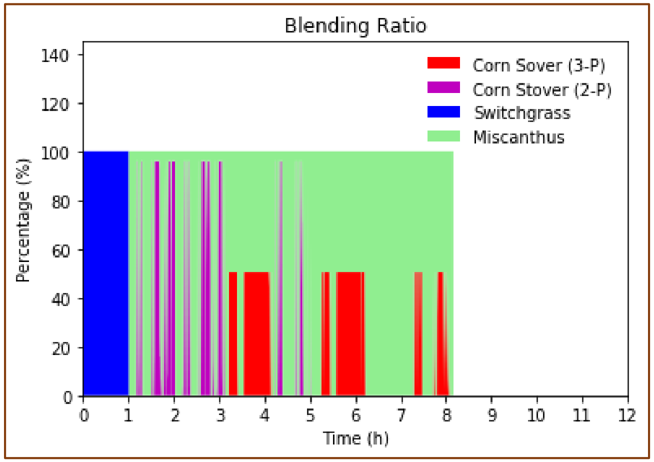
BIOMASS BLEND

Blended biomass that meets process requirements is fed to the reactor every time unit.

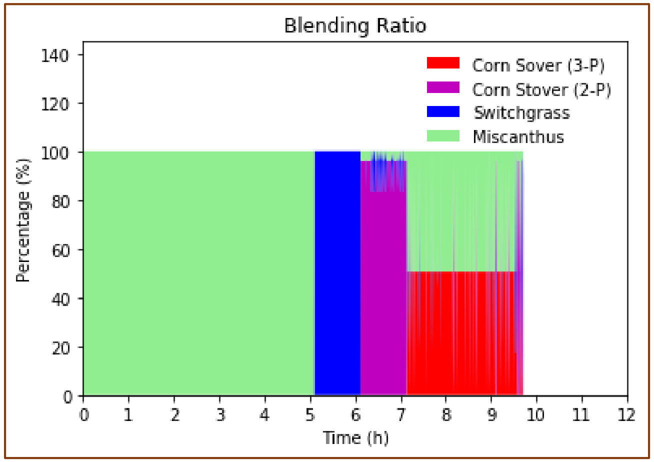
The blends consist mainly of miscanthus because of its low ash content.



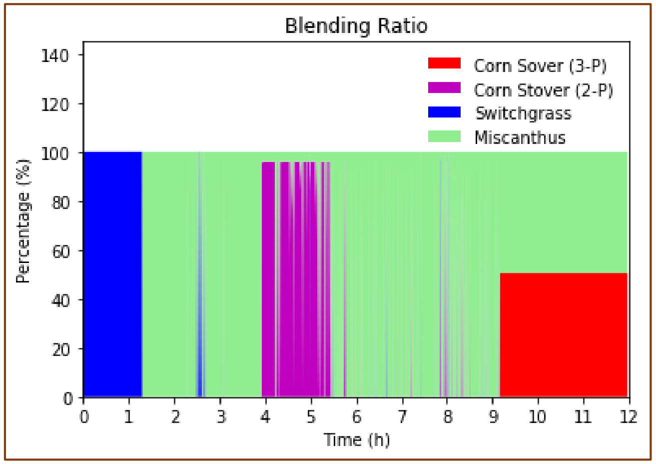
Random Sequence



Short Sequence (P 13)



Long Sequence (P 10)

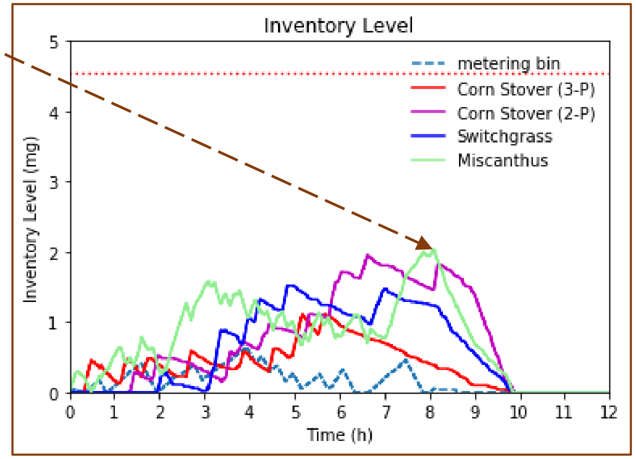


Long Sequence (P 8)

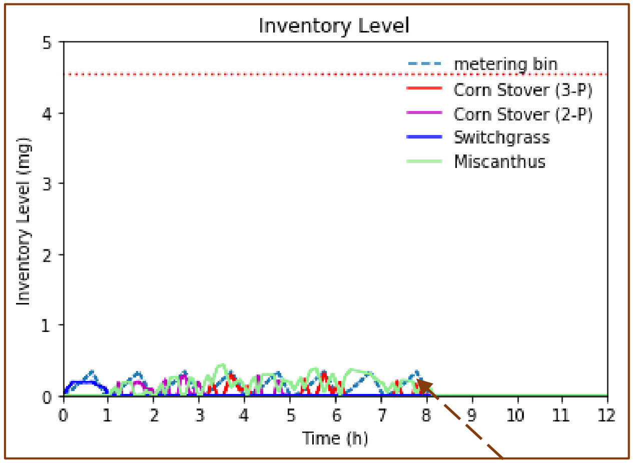
2. APPROACH: Numerical Results

INVENTORY LEVEL

Random sequ. max inv. is 2mg.



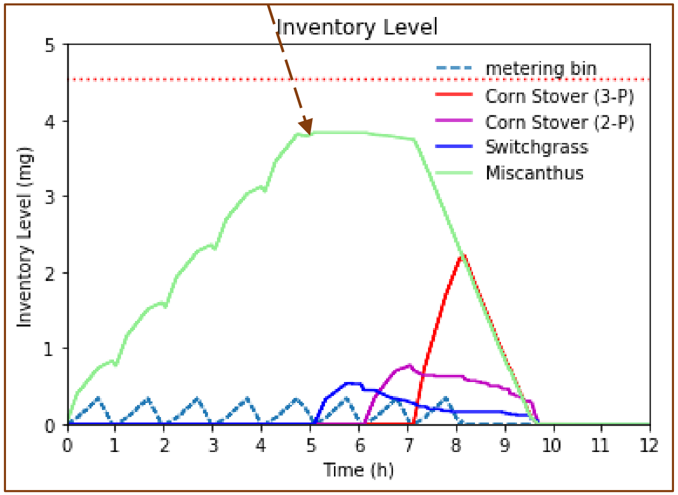
Random Sequence



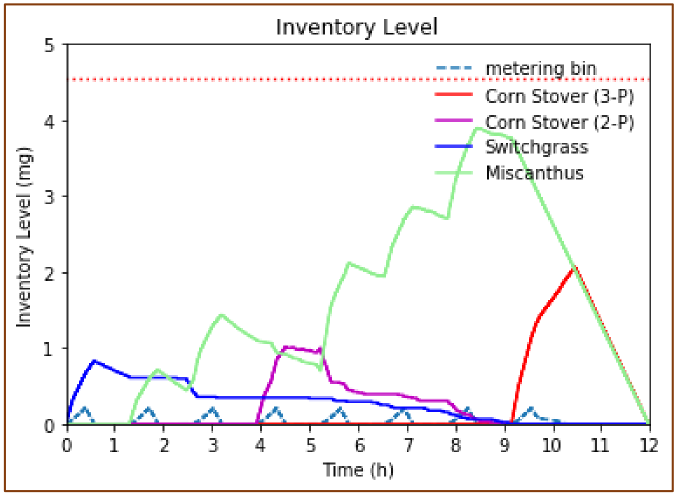
Short Sequence (P 13)

Short sequ. max inv. is 0.4mg.

Long sequ. max inv. is 4mg.



Long Sequence (P 10)



Long Sequence (P 8)

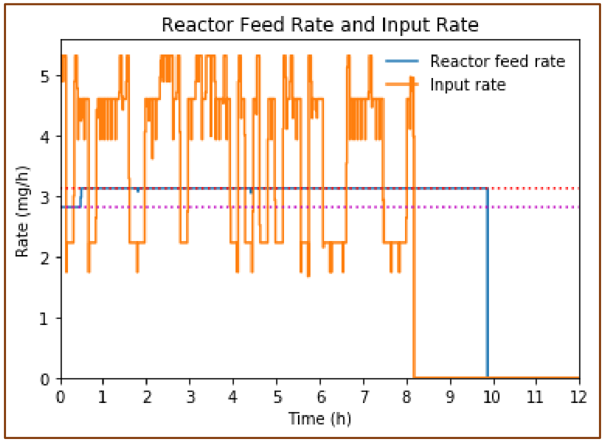
2. APPROACH: Numerical Results

Feeding of the Reactor

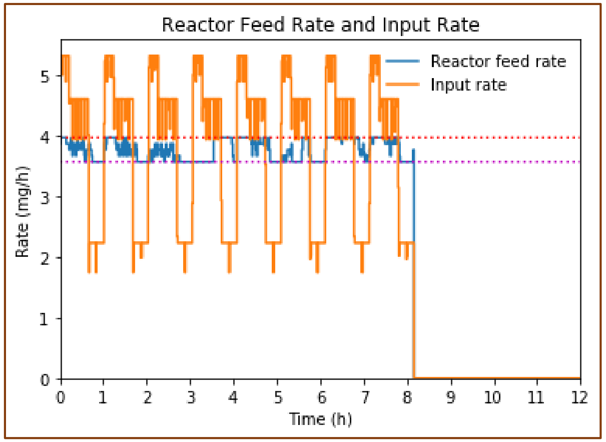
Random sequ. has up to 15% higher processing rate then long sequ.

Proc. rate of short sequ. is 12- 46% higher than that of long and random sequ.

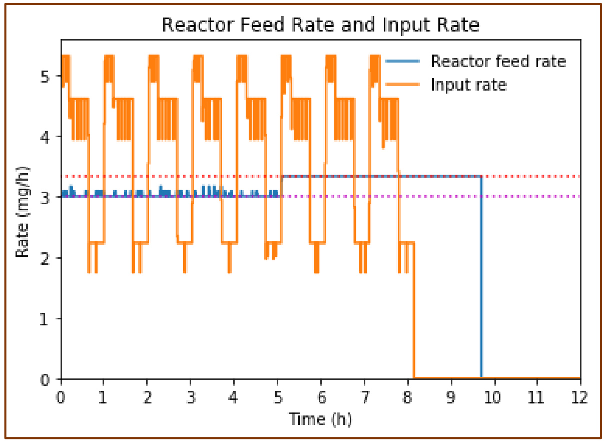
Proc. time of short sequ. is 17-46% shorter than that of long sequ.



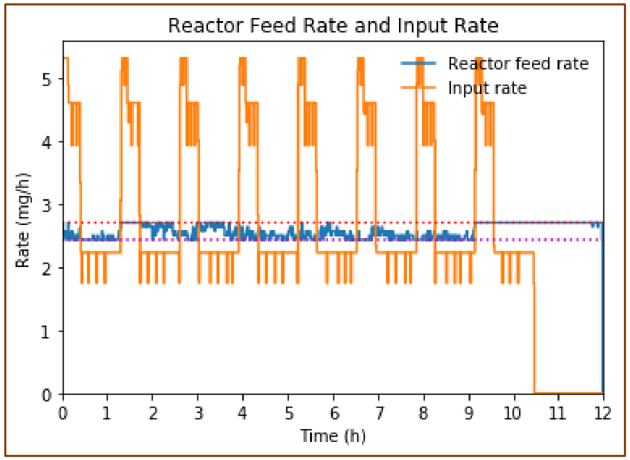
Random Sequence



Short Sequence (P 13)



Long Sequence (P 10)



Long Sequence (P 8)