Version of Record: https://www.sciencedirect.com/science/article/pii/S0360544222005539
Manuscript_3724f2b97024e03f7f9e5cce4e358e95

Optimal Control to Handle Variations in Moisture Content and Reactor In-Feed Rate

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Abstract

The variations in feedstock characteristics, such as moisture and particle size distribution, lead to an inconsistent flow of feedstock from the biomass pre-processing system to the reactor in-feed system. These inconsistencies result in low on-stream times at the reactor in-feed equipment. This research develops an optimal process control method for a biomass pre-processing system comprised of milling and densification operations to provide the consistent flow of feedstock to a reactor's throat. This method uses a mixed-integer optimization model to identify optimal bale sequencing, equipment in-feed rate, and buffer location and size in the biomass pre-processing system. This method, referred to as the hybrid process control (HPC), aims to maximize throughput over time. We compare HPC with a baseline feed forward process control. Our case study based on switchgrass finds that HPC reduces the variation of a reactor's feeding rate by up to 100% without increasing the operating cost of the biomass pre-processing system for biomass with moisture ranging from 10 to 25%. Additionally, HPC reduces the cost of processing biomass by 0.36% to 2.22%, and reduces processing time by 0.35% to 2.24%. A biorefinery can adapt HPC to achieve its design capacity.

Keywords: biomass pre-processing system, biomass moisture variability, optimal process control, mixed-integer linear optimization, buffer control

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Nomenclature

Sets

$\mathcal{C}$ Potential expansion options for storage units, $\mathcal{C} \coloneqq \{0, 0.1, 0.2, \ldots, 1\}$ where 0.1 means capacity is expanded by 10%.

$\mathcal{I}_{\mathcal{G}}$ Grinders

$\mathcal{I}_{\mathcal{M}}$ Storage units

$\mathcal{I}$ Equipment used in a biomass feeding system

$\mathcal{I}_i$ Predecessor of equipment i

$\mathcal{L}$ Biomass moisture levels considered in model

$\mathcal{T}$ Periods in modeling horizon

Indices

$i \in \mathcal{I}$ Equipment locations in the system

$k \in \mathcal{C}$ Potential expansion option.

$s \in \mathcal{L}$ Moisture level

$t \in \mathcal{T}$ Periods

Parameters

α Penalty for adjustment of reactor feeding ($/dry Mg/unit of time)

$\bar{d}_{is}$ Average density of biomass with moisture level s in equipment $i \in \mathcal{I}_{\mathcal{M}}$ (dry Mg/cubic meter)

η Unit sale price of pellets ($/dry Mg)

$\gamma_t \triangleq wh \sum_{s \in \mathcal{L}} d_s j_{st}$ Amount of biomass per meter of bale conveyor at period t (dry Mg/meter).

μ_i Dry matter loss in equipment $i \in \mathcal{I}_{\mathcal{G}}$ (%)

$\overline{m}_i$ Mass capacity of equipment $i \in \mathcal{I}_{\mathcal{M}}$ (dry Mg)

$\overline{v}_i$ Volume capacity of equipment $i \in \mathcal{I}_{\mathcal{M}}$ (cubic meter)

$\overline{x}_{is}$ Capacity of equipment i when processing materials with moisture level of s (dry Mg/unit of time)

θ_s Bypass ratio when processing biomass with moisture level of s (%)

c_{isk} Cost of operating equipment $i \in \mathcal{I}_{\mathcal{M}}$ with processing capacity k for biomass with moisture level s ($)

c_{is} Unit cost of equipment i based on moisture level s ($/unit of time)

d_s Density of biomass bale with moisture level of s (dry Mg/cubic meter)

j_{st} An indicator parameter which takes the value 1 if biomass with moisture level s is processed in period t, and takes the value 0 otherwise

n_s The number of bales with moisture level s

q_s The mass of a bale with moisture level s (dry Mg)

w, h Width and height of a bale (meters)

Decision variables

β_t^+, β_t^- Decision variables to control reactor feeding rate deviations (dry Mg/unit of time).

$\mathbb{M}_{ist}$ Inventory level of biomass with moisture level s in equipment $i \in \mathcal{I}_{\mathcal{M}}$ at period t (dry Mg)

$\mathbb{X}_{ist}$ Outflow of material with moisture level s from equipment $i \in \mathcal{I}_{\mathcal{M}}$ at period t (dry Mg/unit of time)

J_k takes the value 1 if the capacity of an equipment is expanded by $k\%$, takes the value 0 otherwise.

X_{it} Outflow from equipment i at period t (dry Mg/unit of time)

X_t In-feed rate of the system at period t (dry Mg/unit of time)

Y_t Conveyor speed at period t (meters/unit of time)

1. Introduction

Biomass characteristics vary by moisture, composition, particle size, shape, and density. These variabilities often cause poor flowability of materials at pre-processing systems that lead to clogging of equipment [1]. For example, variable moisture content causes variability in particle sizes in attrition mills. Whereas small particles may plug weep holes, larger particles may plug bins. Poor flowability often stems from arching, bridging, and rat-holing in the system [1]. Solid materials have unanticipated physical interactions with equipment, which often cause interruptions in the flow. These interruptions negatively affect down-steam processes.

The variability of biomass characteristics impacts biorefineries in different ways. Variations of particle size and distribution, moisture, ash, and heat contents negatively affect the integration of biomass feeding systems and conversion processes and result in low or unreliable on-stream time and long start-up times. For these reasons, a number of biorefineries, which were planning to ramp-up production, had to delay these plans. For example, Bell [2] and Merrow [3] show that feeding systems reached only 77% of their designed production amount at the end of the first year of operation (see [2] for findings related to general particulate processes and [3] for initial efforts to reveal and communicate drawbacks of particulate processes). Bioenergy experts report that capital expenditures and operating expenses have risen due to operational difficulties of handling biomass. These findings are proven empirically [4] and via engineering perspectives [5]. The challenges outlined here emerge as significant barriers for biomass to become a sustainable source of energy. As a consequence, major commercial biorefineries (e.g., DuPont) have discontinued their production in the U.S. [6]. Furthermore, investors are becoming reluctant to invest in the biofuel industry due to the high risks stemming from variability of biomass characteristics, market, and supply chain [7]. Sustainable operations of a biorefinery under biomass variations remains a challenge [8].

A number of efforts have been made to mitigate the impacts of variations in biomass characteristics and to improve the design throughput of a biofuel conversion process. First, new designs of the equipment in the pre-possessing system have been proposed to improve flowability. There is rich literature examining physical interactions of biomass and equipment design to gain insight towards improving flowability. As an example, Dooley et al. [9]

proposed a rotary shear mechanism to chop biomass efficiently. Engineers alternatively prefer improving existing equipment, usually supported by modeling tools such as the discrete element method (DEM). For example, Ketterhagen et al. [10] used DEM to identify the correct geometry of a hopper to ensure an uninterrupted flow of particles. Crawford et al. [11] investigated the effects of chemical additives, moisture content, particle interaction, and wall friction forces on the flowability of biomass materials. Wu et al. [12] measured physical characteristics of biomass and introduced designs for handling and storage equipment that align with these measurements.

Second, process control via advanced modeling and simulation tools has shown to reduce the negative impacts that variations of biomass characteristics have on achieving the design throughput of a conversion process. Process control shows a prominent potential to identify robust process designs that handle variations in feedstock characteristics and equipment down-time. There are abundant studies in the literature focusing on process control that model inflow and outflow for equipment in consideration. Marino et al. [13, 14] developed data-driven decision support systems, which inform operators regarding the performance of grinders given the moisture content of bales, in-feed rate, and screen size. Jaramillo and Sanchez [15] proposed a mathematical formulation to model outflow from a pre-treatment continuous tubular reactor. Numbi and Xia [16] adopted a system optimization perspective to model optimal processing of high-pressure grinding rolls. Hartley et al. [17] emphasized the effect of biomass physical characteristics on the performance of a pre-processing system by modeling biomass flow via a discrete-event simulation.

Third, taking preventative measures reduces equipment down-time due to variations of biomass characteristics. For instance, processing high-moisture bales at a lower rate minimizes the risk of clogging. We regard preventative measures as practical applications that improve the reliability of biomass pre-processing systems. One area in reliability is concerned with minimizing variability in production systems by adjusting control variables (e.g., feed at a lower rate). Strong mathematical assumptions, however, limit the applicability of the models in this area. Das et al. [18] analyzed a production system where random failures of equipment occur. They provide a closed-form expression of the economic production lot-size. Li and Meerkov [19] suggested bounds on throughput variances so that a proper serial

line of production can be designed. Assaf et al. [20] and Colledani et al. [21] analyzed the variability of output from unreliable equipment in single-stage or simplified multi-stage systems.

Last, but not least, changing the underlying structure of feeding systems by relocating equipment and storage areas has shown to improve the design throughput of a conversion process. For example, adding buffers to the system ensures a smooth flow. Indeed, improving production systems via investigating the effectiveness of buffer size and location is a rich area of research. A number of studies make probabilistic assumptions concerning processing time and biomass supply. These models, however, are generally limited due to strong assumptions. Tempelmeier [22] investigated (continuous) flow of materials in production systems and discussed different algorithms to determine optimal buffer sizes and their locations. Tan and Gershwin [23] analyzed a two-stage continuous-flow system by assuming that transitions among states are Markovian and one buffer with finite capacity is present between stages. Similarly, Turki et al. [24] determined an optimal buffer size for a single-product machine with random failures. In Hosseini and Tan [25], each stage in a two-stage system has different states of processing with general distribution of transition times. The authors developed a mixed-integer linear programming model to determine the optimal level of buffer by maximizing profit.

The efforts listed above have some limitations. Equipment design and process control are usually tied to a single equipment. In other words, these efforts tend to ignore the impacts of biomass flow on the performance of an integrated feeding and pre-processing system. However, it is crucial that the design of a hopper or the control of a grinder are informed by the performance of the predecessor and successor equipment. This is of significance to make system-wide optimal decisions. Moreover, studies concerning the reliability and buffer analysis are usually coupled with strong and unrealistic mathematical assumptions. Being tied to single equipment and strong mathematical assumptions makes the above-mentioned approaches inappropriate to model and analyze biomass feeding systems.

We point out a few characteristics of our approach that are novel and distinguish it from other works in the literature. First, this study mitigates the limitations of the above-mentioned approaches by developing a novel, system-level model of biomass processing.

The proposed model considers every stage of a biomass feeding system, beginning with the feeding of biomass bales, to biomass processing and feeding of the reactor. We develop and analyze process control strategies to handle the moisture variation in feedstock characteristics and reactor in-feed rate. As a result, our proposed model can be utilized to understand appropriate control method to handle moisture variations in the biomass for an integrated biorefinery

Second, our approach considers sequencing of bales. In practice, high-moisture bales are processed slowly to avoid clogging in grinders. Such a practice becomes a bottleneck to reaching higher target rates. One way to overcome this challenge is to process bales following patterns that repeat frequently and begin with low-moisture bales. This allows inventory to build-up in the downstream of the milling system. This inventory is consumed when processing high-moisture bales. Through this research, we analyze the impact that different sequences of bales have on achieving the maximum feeding rate, minimizing buffer size, and minimizing the cost of operating the system. To the best of our knowledge, there is no study in the literature that has analyzed the effect of bale sequencing on the performance of biomass processing systems.

Third, our approach controls buffer size and location as the means for managing the variability of biomass characteristics and maintaining a continuous feeding of feedstock to a reactor (at the maximum possible feeding rate). As the above literature review points out, buffer management in production systems is a critical task as buffers serve to match supply (inflow) with demand (outflow). Smooth processes can only be created with the introduction of buffers. However, a process benefits from buffers when resulting costs of buffer installation are lower than the benefits gained through the installations. Our work analyzes the trade-off between costs of adding marginal capacity in storage units and the reduction in the variability of reactor feeding. To the best of our knowledge, there is no study that has analyzed such a trade-off for biomass pre-processing systems.

Finally, our work exhibits how to formulate optimal control approaches using linear and mixed-integer linear programmings. These formulations are general to a large extent and can be applied to several biomass feeding systems. We use these models to develop and compare two different control approaches, the hybrid process control (HPC), which aims to

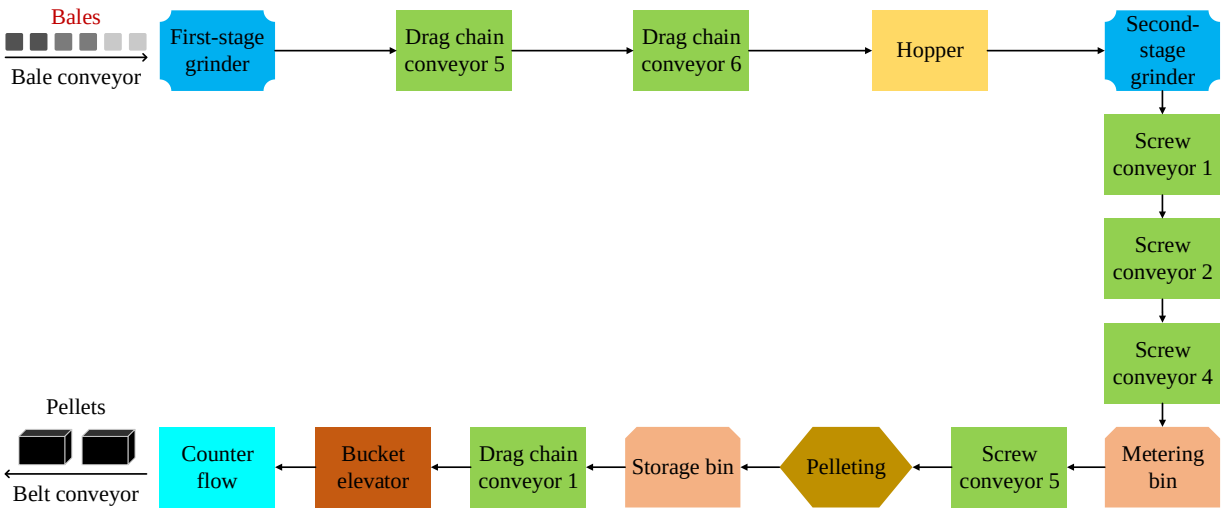
maximize throughput over time, and a state-of-the-art baseline feed forward process control (BFFPC). Through this research, we provide a cost/benefit analysis for BFFPC and HPC under different settings of a biomass feeding system. In summary, our study is uniquely positioned to devise a control approach for biomass feeding systems.

In summary, this research makes novel contributions to the literature and communicates a number of significant managerial insights. We convey that HPC is a potential solution to reduce the variation of reactor feeding rate without increasing cost.

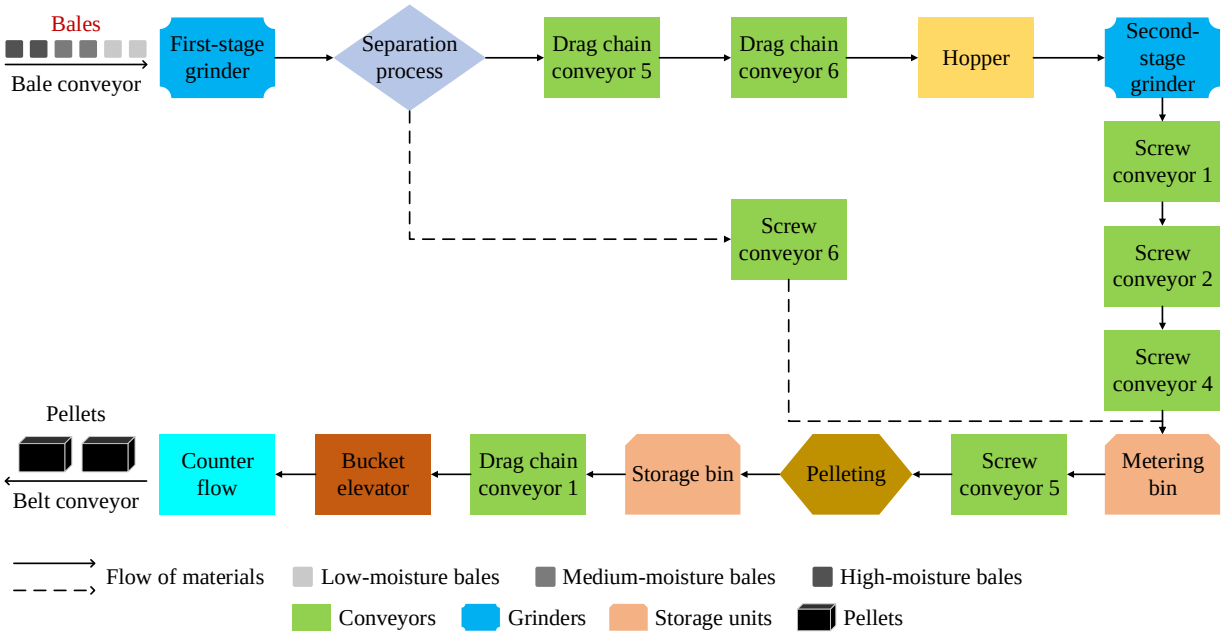
2. Material and Methods

2.1. Feedstock Pre-processing Description

Feedstock pre-processing in this study includes two-stage size reduction and densification. The first-stage size reduction uses a grinder to break the bale into smaller particles. The second-stage size reduction further reduces the particle size via a hammer mill. Densification converts biomass to pellets. Figures 1a and 1b illustrate the system with equipment (throughout the text, we use 'storage units' to refer to both 'metering bin' and 'storage bin'. 'Storage bin' and 'metering bin' point to individual equipment). We refer the interested readers to a study of biomass feedstock supply system design and analysis by [26] for additional information about equipment and feedstock pre-processing systems. A supplemental file presents figures of several equipment and process demonstration unit (PDU). Table S1 and S2 list some specifications for equipment.



(a) Without fractional milling



(b) With fractional milling

Figure 1: A biomass pre-processing system

The feedstock pre-processing system that we utilize in this study has two different designs based on whether a separation unit is utilized between first-stage and second-stage grinding. Processing without fractional milling does not have a separation process. After being processed in the first-stage grinder, materials go through the second-stage grinder for further size reduction. Such a practice produces fines that are prohibitive for the successful

operation of the system. In processing with fractional milling, following first-stage grinding, a separation unit separates small-sized particles and pushes them to a storage unit (we call the percentage of small-sized particles the "bypass ratio"). Such a practice results in tighter particle size distribution, a minimum amount of fines, and reduced energy consumption [27].

2.2. Description of Proposed Control Method in the Feedstock Pre-processing System

Primary control variables in the feedstock pre-processing system are: (*i*) screen sizes in grinders; (*ii*) in-feed rate (amount of material processed per unit of time); (*iii*) mill speed in grinders; (*iv*) discharge rates from storage units; (*v*) feeding rate of pellet mill; and (*vi*) amount of moisture to add to the pellet mix. Operators usually adjust these variables to ensure the uniformity of particle sizes and increase pellet quality. Since screen size and moisture requirements can be determined in advance based on pellet particle size and quality requirements, we fix the value of the following control variables to pre-determined values – screen size associated with first- and second-stage size reduction and moisture.

The proposed control method (e.g., HPC) is an adaption of the feedback loop control and incorporates additional biomass process specific controls, examples of which are given in studies of refrigerators/cooling systems [28] and demand-side management systems [29]. Thus, HPC is a control approach whose primary goal is to meet a desired output response by adjusting bale sequencing decisions, biomass in-feed rate of different equipment, and buffer location and size. Consider the feedstock pre-processing design with fractional milling. Processing of bales with different moisture leads to additional operational constraints. For example, in-feed rate of second-stage grinding is constrained by moisture content of biomass since high moisture biomass is fed at a slow rate to prevent clogging in the system. Low moisture biomass is processed faster. This variation in moisture causes a fluctuation in the feedstock processing and reactor feeding rates.

The fluctuation of the reactor feeding rate can be handled in the proposed HPC method in the following way. First, the operator characterizes the bale based on its moisture range (e.g., high-, medium-, and low-moisture ranges). Second, the operator decides when to process low-, medium-, or high-moisture bales, as well as when to build-up/use the buffer to maintain a continuous feeding of the reactor. By simultaneous optimization of bale sequencing, in-feed

rate, and buffer location and size, the HPC determines an optimal trajectory that maintains the continuous feeding of a reactor. If the current process's buffer size (e.g., metering bin) is not sufficient, then optimization also decides by how much to increase the buffer size (see Figure S8a).

The proposed HPC method is compared with the state-of-the-art BFFPC to demonstrate the differences and benefits of the proposed method. BFFPC faces the same operational constraints caused by moisture. This BFFPC method maximizes the total throughput over time but does not necessarily maintain a continuous feeding of the reactor. The BFFPC operates as follows. First, the operator characterizes bales based on moisture range, but feeds bales in an unsystematic way. That means, bales are not arranged in a sequence according to their moisture contents. We will henceforth use the term "random pattern" to refer to this arrangement. Second, in contrast to the HPC method, BFFPC finds an optimal trajectory that maximizes throughput by optimizing in-feed rate, but it does not control buffer location and size (see Figure S8b).

We summarize the commonalities and differences of BFFPC and HPC in Table S3.

2.3. Optimization Model Development

The optimization model identifies the minimum time to process a fixed number of bales using HPC and BFFPC under various operational constraints. The optimal trajectory to process a fixed number of bales is found via an algorithm as shown in Figure S9. The goal is to shorten the modeling horizon iteratively until no better solution is found. In each iteration of this algorithm, an optimization model is solved. The implementation of this algorithm is described in the supplementary material. Throughout the text, we use dry Mega gram (dry Mg) as mass unit.

2.3.1. MILP model for HPC

The optimization model we make reference to in Figure S9 is defined by Equations (1)-(21) and corresponds to HPC. The objective function (1) minimizes the variations of a reactor's feeding, maximizes the throughput of the system, and determines the optimal location and size of the buffer. The first term in the objective maximizes the throughput of the system by maximizing $\eta X_{|\mathcal{I}|t}$, the hypothetical revenue gained by producing/selling one unit of pellet

at period t. The second term in the objective minimizes the volatility of the feeding rate of the reactor to ensure a continuous and smooth feeding of the reactor, a key success indicator for a biomass feeding system. The last term in the objective minimizes the cost of expanding the capacity of storage units.

$$\max \sum_{t\in\mathcal{T}} \left[\eta X_{|\mathcal{I}|t} - \alpha\left(\beta_t^+ + \beta_t^-\right)\right] - \sum_{i\in\mathcal{I}_\mathcal{M}} \sum_{k\in\mathcal{C}} \sum_{s\in\mathcal{L}} \sum_{t\in\mathcal{T}} c_{isk} j_{st} J_k \tag{1}$$

We use Equations (1)-(21) to obtain optimal trajectories of system in-feed rate, reactor feeding rate, and inventory in storage units. The operating cost of equipment, however, has unit of \$/hour. Thus, after obtaining the optimal trajectories, we calculate the corresponding cost of operating the system via

$$\sum_{i\in(\mathcal{I}-\mathcal{I}_\mathcal{M})} \sum_{s\in\mathcal{L}} \sum_{t\in\mathcal{T}} c_{is} + \sum_{i\in\mathcal{I}_\mathcal{M}} \sum_{k\in\mathcal{C}} \sum_{s\in\mathcal{L}} \sum_{t\in\mathcal{T}} c_{isk} j_{st} J_k \tag{2}$$

given the optimal value of J_k. Therefore, the optimal cost we present in our numerical analyses considers only system operating costs.

Capacity constraints: Each equipment has processing capacities, which we model via Eq.(3-5).

$$X_{it} \leq \sum_{s\in\mathcal{L}} j_{st} \overline{x}_{is} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{3}$$

$$\sum_{s\in\mathcal{L}} \mathbb{M}_{ist} \leq \overline{m}_i \left(1 + \sum_{k\in\mathcal{C}} k J_k\right) \qquad \forall i \in \mathcal{I}_\mathcal{M}, \forall t \in \mathcal{T} \tag{4}$$

$$\sum_{s\in\mathcal{L}} \frac{\mathbb{M}_{ist}}{\bar{d}_{is}} \leq \overline{v}_i \left(1 + \sum_{k\in\mathcal{C}} k J_k\right) \qquad \forall i \in \mathcal{I}_\mathcal{M}, \forall t \in \mathcal{T} \tag{5}$$

$$1 \geq \sum_{k\in\mathcal{C}} J_k. \tag{6}$$

Constraints (3) indicate that the outflow of biomass from each equipment should not exceed its pre-determined processing capacity, which is driven by the moisture level of the biomass processed at each period. Constraints (4) limit the mass of biomass inventoried and constraint (5) limit the volume of biomass inventoried in a storage unit. This consideration is necessary because for loose biomass (low density), the volume capacity is restrictive, whereas mass capacity turns out to be restrictive in the case when biomass is highly dense. These

constraints also consider the expansions of storage units' capacities in mass and volume dimensions. We calculate the average density of biomass $\bar{d}_{is}$ as the weighted average of biomass densities conveyed via the two conveyors connected to a metering bin. The corresponding weights are θ_s and $1-\theta_s$. Constraint (6) ensures that only one capacity expansion is chosen. If we desire to run HPC without the capacity expansion option, we simply adjust constraint (6) by replacing its left-hand side with 0.

Operational constraints: The system under consideration has operational capacities related to system in-feed. The in-feed rate of the system refers to the amount of biomass fed to the system in a period. Constraint (7) calculates the in-feed rate based on the physical dimensions of a bale, its density, and conveyor speed. Constraint (8) ensures that every bale is processed. β_t^+ and β_t^- calculate the change of reactor feeding rate from one period to the next. If $X_{|\mathcal{I}|t} - X_{|\mathcal{I}|t-1} > 0$, $\beta_t^+ > 0$ and $\beta_t^- = 0$, otherwise, if $X_{|\mathcal{I}|t} - X_{|\mathcal{I}|t-1} < 0$, $\beta_t^+ = 0$ and $\beta_t^- > 0$. In the case when the feeding of a reactor does not change in successive time periods, $\beta_t^+ = \beta_t^- = 0$.

$$X_t = \gamma_t Y_t \qquad \forall t \in \mathcal{T} \tag{7}$$

$$\sum_{t \in \mathcal{T}} j_{st} X_t = q_s n_s \qquad \forall s \in \mathcal{L} \tag{8}$$

$$\beta_t^+ - \beta_t^- = X_{|\mathcal{I}|t} - X_{|\mathcal{I}|t-1} \qquad \forall t \in \mathcal{T} \tag{9}$$

Flow balance constraints: Feeding system is essentially a flow system that needs to satisfy flow balance constraints. Constraint (10) computes the outflow from the grinders. The outflow is reduced by the dry matter losses in the grinders. Constraint (11) shows that the amount of biomass that does not bypass will continue flowing on drag chain conveyor 5 (d.c.5). The biomass that bypasses the separation unit flows on screw conveyor 6 (s.c.6) that feeds the metering bin, as indicated by constraint (12). Constraint (13) represents that flow balance (flow in equals flow out) for other equipment.

$$X_{it} = \sum_{p \in \mathcal{I}_i} (1 - \mu_i) X_{pt} \qquad \forall i \in \mathcal{I}_{\mathcal{G}}, \forall t \in \mathcal{T} \tag{10}$$

$$X_{it} = \sum_{p \in \mathcal{I}_i} \left(1 - \sum_{s \in \mathcal{L}} j_{st} \theta_s\right) X_{pt} \qquad i = \text{d.c.5}, \forall t \in \mathcal{T} \tag{11}$$

$$X_{it} = \sum_{p \in \mathcal{I}_i} \left(\sum_{s \in \mathcal{L}} j_{st} \theta_s\right) X_{pt} \qquad i = \text{s.c.6}, \forall t \in \mathcal{T} \tag{12}$$

$$X_{it} = \sum_{p \in \mathcal{I}_i} X_{pt} \qquad \forall i \in \mathcal{I} - \{\text{d.c.5, s.c.6}, \mathcal{I}_{\mathcal{M}}, \mathcal{I}_{\mathcal{G}}\}, \forall t \in \mathcal{T} \tag{13}$$

Inventory balance constraints: Constraint (14) is the mass balance constraint for storage units. Constraint (15) finds the total outflow from each storage unit at period t. We assume that the system does not carry initial inventory in storage units, presented by constraint (16).

$$\mathbb{M}_{ist} = \mathbb{M}_{ist-1} + \sum_{p \in \mathcal{I}_i} j_{st} X_{pt} - \mathbb{X}_{ist} \qquad \forall i \in \mathcal{I}_{\mathcal{M}}, \forall s \in \mathcal{L}, \forall t \in \mathcal{T} \tag{14}$$

$$X_{it} = \sum_{s \in \mathcal{L}} \mathbb{X}_{ist} \qquad \forall i \in \mathcal{I}_{\mathcal{M}}, \forall t \in \mathcal{T} \tag{15}$$

$$\mathbb{M}_{is0} = 0 \qquad \forall i \in \mathcal{I}_{\mathcal{M}}, \forall s \in \mathcal{L} \tag{16}$$

Non-negativity constraints: The following are the non-negativity constraints.

$$0 \leq X_t \qquad \forall t \in \mathcal{T} \tag{17}$$

$$0 \leq X_{it} \qquad \forall i \in \mathcal{I}, \forall t \in \mathcal{T} \tag{18}$$

$$0 \leq Y_t \qquad \forall t \in \mathcal{T} \tag{19}$$

$$0 \leq \mathbb{X}_{ist}, \mathbb{M}_{ist} \qquad \forall i \in \mathcal{I}_{\mathcal{M}}, \forall s \in \mathcal{L}, \forall t \in \mathcal{T} \tag{20}$$

$$0 \leq \beta_t^+, \beta_t^- \qquad \forall t \in \mathcal{T} \tag{21}$$

We refer to the MILP formulation above ((1), (3) to (21)) as **Problem H** for HPC.

Notice that this version of HPC includes fractional milling. If we desire to use HPC without fractional milling, we make the following adjustments in the above model. We set $\theta_s = 0, \forall s \in \mathcal{L}$, which impacts constraints (11) and (12). Fixing the value of $\theta_s = 0$ also impacts constraint (5) since θ_s and $1 - \theta_s$ are used as weights in calculations of $\bar{d}_{is}$. Since screw conveyor 6 does not exist in this problem setting, we deduct the cost of screw conveyor

6 from the cost expression (2).

2.3.2. LP model for BFFPC

We develop an LP formulation of BFFPC by updating the model introduced above for HPC. In this section, we only list the modifications we make.

Objective function: The objective function of BFFPC focuses on maximizing the amount of biomass processed within the time horizon.

$$\max \sum_{t \in \mathcal{T}} \left[\eta X_{|\mathcal{I}|t} \right] \tag{22}$$

We compute the cost of operating the system via

$$\sum_{i \in \mathcal{I}} \sum_{s \in \mathcal{L}} \sum_{t \in \mathcal{T}} c_{is} \tag{23}$$

Capacity constraints of storage units: Since BFFPC does not consider expansion of storage units capacities, we replace constraints (4) and (5) of HPC with constraints (24) and (25), as shown below.

$$\sum_{s \in \mathcal{L}} \mathbb{M}_{ist} \leq \overline{m}_i \qquad \forall i \in \mathcal{I}_{\mathcal{M}}, \forall t \in \mathcal{T} \tag{24}$$

$$\sum_{s \in \mathcal{L}} \frac{\mathbb{M}_{ist}}{\bar{d}_{is}} \leq \overline{v}_i \qquad \forall i \in \mathcal{I}_{\mathcal{M}}, \forall t \in \mathcal{T} \tag{25}$$

Notice that BFFPC does not use variables J_k; thus, constraint (6) is not considered. Since BFFPC does not aim to control the variations of a reactor's feeding rate, variables β_t^+, β_t^- and constraints (9) and (21) are not considered as well.

The remaining of the constraints are the same in both HPC and BFFPC model formulations. We refer to the LP formulation presented above (e.g., (22), (3), (7), (8), (10)-(20), (24), and (25)) as **Problem B** for BFFPC.

2.4. Solution Approach

We implement the LP and MILP models in Julia (Bezanson et al. [30]), utilizing JuMP modeling language (Dunning et al. [31]), and use the Gurobi solver (see Gurobi optimization [32]). We execute the models on a computer that has 32 GB RAM and an Intel(R) Xeon(R) CPU E5-1620 v2 CPU running at 3.7 GHz. We use a 1-minute granularity in

the optimization. We set a 30-minute time limit and 1% optimality gap for Gurobi. The minimum, average, and maximum CPU time to solve a single LP (**Problem B**) are 0.282, 0.405, and 0.642 seconds. The corresponding minimum, average, and maximum CPU time to solve the MILP (**Problem H**) are 0.318, 0.721, and 1.774 seconds. The running time of the algorithm presented in Figure S9 varies from 18.87 seconds to 66.59 seconds. This variation results from different patterns of feeding bales to the system.

3. Case Study

3.1. Technical Process Data

We utilize technical process data from the PDU at Idaho National Laboratory (INL). Table 1 summarizes the data collected by analyzing historical grinding and densification experiments of switchgrass at INL's PDU. The data is grouped based on the moisture level of biomass and based on processes. Problem parameters, such as moisture level, biomass density, dry matter loss, moisture loss and energy consumption are uncertain. Thus, in Table 1, we report the corresponding average values.

Notice that grinders consume more energy when biomass has a high moisture level [33]. Due to grinding, biomass loses moisture. Wet material loss is the largest for biomass with high moisture levels [34]. Since particle sizes alter during grinding, material density changes. Bulk density of biomass diminishes during first-stage grinding as biomass in bale form is tapped. In contrast, density increases during the second-stage grinding as the particles get smaller. As noted before, wet biomass is processed slow to prevent clogging. Hence, the maximum in-feed rate of grinders decreases for high-moisture materials, which negatively impacts the processing capacity of the system. There are several options to select screen size combinations for coupled grinders. Experiments at PDU show that it is the best practice to use screens with a diameter of 76.2-mm and 11.11-mm in first-stage and second-stage grinders, respectively [35]. Utilizing these screens minimizes the amount of fine particles.

			Moisture Levels		
			High	**Medium**	**Low**
Bale	Avg. moisture (%)		25	17.50	10
	Avg. dry bulk density (dry Mg/cubic meter)		0.144	0.144	0.144
First-stage Grinder	Operating conditions	Screen size (mm)	76.2	76.2	76.2
		Avg. dry bulk density (dry Mg/cubic meter)	0.144	0.144	0.144
		Avg. moisture (%)	25	17.5	10
	Process performance	Avg. energy consumption (kWh/dry Mg)	25.68	21.95	7.10
		Avg. moisture loss (%)	4.77	3.00	0.5
		Avg. dry matter loss (%)	1.50	1.50	1.50
		Avg. bulk density change (dry Mg/cubic meter)	-0.09	-0.10	-0.11
		Maximum in-feed rate (dry Mg/hour)	2.20	4.53	5.23
Separation Unit	Operating conditions	Screen size (mm)	6.35	6.35	6.35
		Avg. dry bulk density (dry Mg/cubic meter)	0.053	0.041	0.039
		Avg. moisture (%)	20.23	14.50	9.50
	Process performance	Avg. moisture loss (%)	0.71	0.50	0.00
		Avg. bypass ratio (%)	40.48	44.98	49.98
Second-stage Grinder	Operating conditions	Screen size (mm)	11.11	11.11	11.11
		Avg. dry bulk density (dry Mg/cubic meter)	0.053	0.041	0.039
		Avg. moisture (%)	19.52	13.99	9.50
	Process performance	Avg. energy consumption (kWh/dry Mg)	49.71	16.58	14.67
		Avg. moisture loss (%)	4.00	3.00	0.7
		Avg. dry matter loss (%)	0.50	0.50	0.50
		Avg. bulk density change (dry Mg/cubic meter)	0.066	0.082	0.090
		Maximum in-feed rate (dry Mg/hour)	1.59	2.80	5.23
Pelleting Equipment	Operating conditions	Avg. dry bulk density (dry Mg/cubic meter)	0.119	0.123	0.129
		Avg. moisture (%)	15.52	10.99	8.80
	Process performance	Avg. energy consumption (kWh/dry Mg)	90.39	60.63	55.12
		Avg. moisture loss (%)	3.92	1.50	0.00
		Avg. bulk density change (dry Mg/cubic meter)	0.547	0.542	0.537
		Maximum in-feed rate (dry Mg/hour)	3.33	3.81	4.76

Table 1: Technical process-related data used as input for BFFPC and HPC

Table 1 also presents the technical process data for the separation unit. The bypass ratio is smallest in the case when biomass is highly moist. When materials are wet, they

tend to be cohesive, cling to one another, and end up creating aggregates. This reduces the amount of materials bypassing the separation unit. Materials lose moisture at this stage as well. Wet materials lose the largest amounts of moisture during separation. Table 1 also lists the technical process data for densification equipment (via pelleting mechanism). Pelleting equipment consumes the highest amount of energy in a biomass feeding system [36]. When material is wet, energy consumption rises. Moisture loss occurs due to heating during densification. Wet materials lose the highest amounts of moisture during pelletization. Operators feed pelleting equipment at a lower rate when material is highly moist to ensure the production of high-quality pellets.

Every equipment of PDU has a processing capacity of 13.61 dry Mg/hour, with the exception of the first-stage grinder, second-stage grinder, and pelleting. Metering and storage bins have a storage capacity of 4.54 dry Mg. The volume capacity of these storage units is 24.07 cubic meter. This number is determined based on the the machines utilized at INL PDU (details are available in the supplementary material). The width , height, and length of a bale are 1.22, 0.91, and 2.44 meters, respectively. The average mass of a bale is 0.392 dry Mg. The sale price of pellets is \$77.16/dry Mg. This number is assumed based on the feedstock supply chain techno economic analysis [26]. The proposed selling price includes market profit. We estimate the unit cost of adjusting the feeding of a reactor is \$5.51/(dry Mg/minute). This is a conservative assumption to reflect the cost of negative impact of variation in reactor in feed rate to the downstream conversion process. This cost is sufficiently large to minimize the deviation of reactor's feeding rate. We conduct a thorough sensitivity analysis with different values of sale prices for the pellets and the unit cost of adjustment of reactor feeding. We observe that solutions are not sensitive to these parameters.

3.2. Techno-economic Data

We use the Biomass Logistics Model (BLM) to estimate input cost data, such as the unit operation cost of pre-processing, handling, and storing used in the model . BLM is an integrated framework that quantifies the impacts of feedstock supply system design on costs, greenhouse gas emissions, and energy consumption. It uses a system dynamics simulation

model to simulate the flow of biomass through the whole supply chain, track the change in biomass physical characteristics during operations, and adjust cost/benefit of the engineered system resulting from these operations. Cafferty et al. [37] provide a short description of the BLM. They present a case study for corn stover in which feedstock related costs are estimated from the point of harvest to conversion to fuel. Other studies use BLM to estimate the cost of feedstock processing systems [17], to evaluate whether biorefineries and biomass supply chains could achieve the 2017 design target [38], and to provide managerial insights about siting of biorefineries [39]. We use BLM to estimate the cost of operating a feeding system in \$/hour (see Table S2). Table S1 presents other input data collected at INL's PDU.

In the case when the capacity of the storage unit expands, the corresponding operation cost per minute increases. We use the following scaling rule [40] .

$$\frac{c_{is}}{c_{isk}} = \left(\frac{\overline{m}_i}{(1+k)\overline{m}_i}\right)^{0.6} \qquad \forall i \in \mathcal{I}_{\mathcal{M}}, \forall s \in \mathcal{L}, \forall k \in \mathcal{C} \tag{26}$$

to estimate the new costs. In (26), the coefficient 0.6 represents the effect of economies of scale. It means that when capacity of a storage unit is increased by 1 unit, storage unit operation cost does not increase linearly, rather increases in the order of 0.6 This assumption is based on scale of economies [40] of various equipment type utilized in different production processes.

4. Numerical Analysis

In this section, we present the results from implementing the models developed for process design, namely BFFPC and HPC, with and without fractional milling. We compare the performance of BFFPC and HPC by investigating: (i) the optimal trajectories; (ii) the average reactor feeding rate and its variability; (iii) the effect of buffer size expansion and location on system's performance; (iv) the cost of operating the system; and (v) the minimum time to process all bales.

We assume that a total of 200 bales are to be processed in the feeding system. Of these, 60 are low-moisture bales, 100 are medium-moisture bales, and 40 are high-moisture bales. These bales are processed in HPC following different patterns. For example, our "Baseline" pattern begins by processing six low-moisture bales, followed by ten medium-moisture bales,

and finally, processes four high-moisture bales. This pattern is repeated 10 times to process all 200 bales. This pattern is known as 6L,10M,4H X10. BFFPC processes the same number of bales with the same moisture distribution. However, bales are not sequenced according to their moisture level. The feeding pattern is determined randomly and known as "random pattern" in this section.

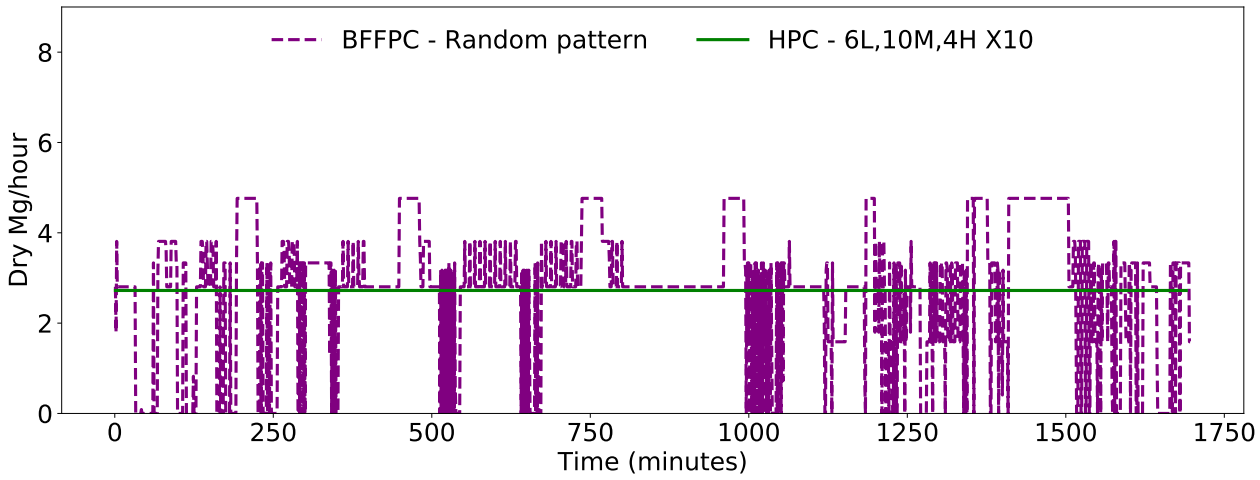
The following is a list of performance metrics we use to compare HPC and BFFPC:

- Maximum inventory (*Max. Inv.*) in storage units is $\max_t \sum_{s\in\mathcal{L}} \mathbb{M}_{ist}, \forall i \in \mathcal{I}_{\mathcal{M}}$.
- Average reactor feeding (*Av. Feed.*) is $\frac{\sum_{t\in\mathcal{T}} X_{|\mathcal{I}|t}}{|\mathcal{T}|}$.
- Variability of reactor's feeding (*Coef. Var.*) is measured via the coefficient of variation of $X_{|\mathcal{I}|t}$, which is $\frac{\text{std}\left(X_{|\mathcal{I}|t}\right)}{\left(\frac{\sum_{t\in\mathcal{T}} X_{|\mathcal{I}|t}}{|\mathcal{T}|}\right)}$ where std is standard deviation operator.
- Cost of operating systems (*Cost*) for HPC and BFFPC is calculated via (2) and (23), respectively.
- Minimum time to process 200 bales (*Min. Time*).

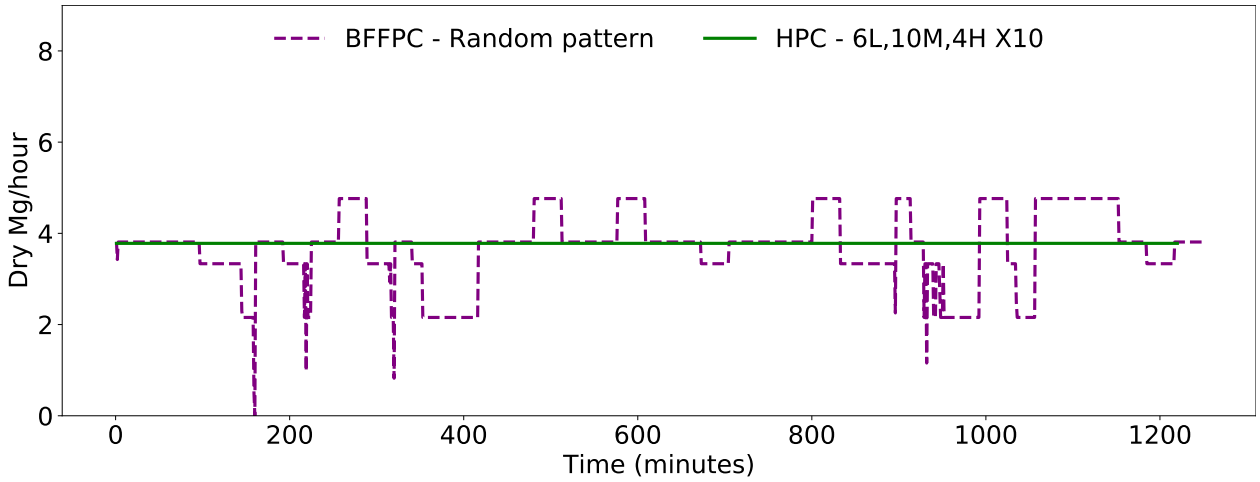
There are other studies that use the coefficient of variation to measure the variability in production systems, examples of which are given in systems reliability literature [41, 19]. Coefficient of variation shows the extent of deviation from average performance in a process. In our case, it presents variations of reactor's feeding rate from one period to the next.

4.1. Optimal trajectories of feeding rate of reactor, in-feed rate, and inventory

In this section, we illustrate the optimal trajectories of a reactor's feeding rate, a system's in-feed rate, and the inventory level. Figure 2a illustrates the optimal trajectories of reactor's feeding rates for BFFPC and HPC for the process design without fractional milling. Reactor's feeding rate in BFFPC varies from 0 to 5 dry Mg/hour, whereas it is constant in HPC. In the process with fractional milling, BFFPC feeds the reactor at a rate ranging from 2 dry Mg/hour to 5 dry Mg/hour, whereas the HPC feeds the reactor at a constant rate (see Figure 2b). These results indicate that HPC reduces the variation of a reactor's feeding rate by 100%, regardless of whether fractional milling is utilized. We further observe that processing times of HPC are slightly shorter than those of BFFPC. It is observed that BFFPC without fractional milling exhibits more variability as compared to BFFPC with fractional milling.



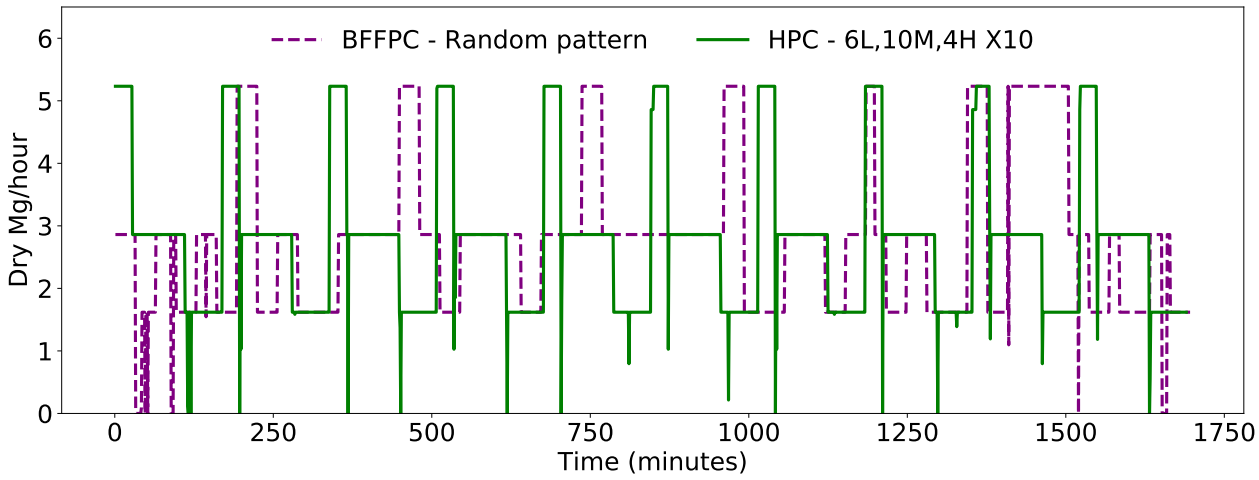
(a) Without fractional milling



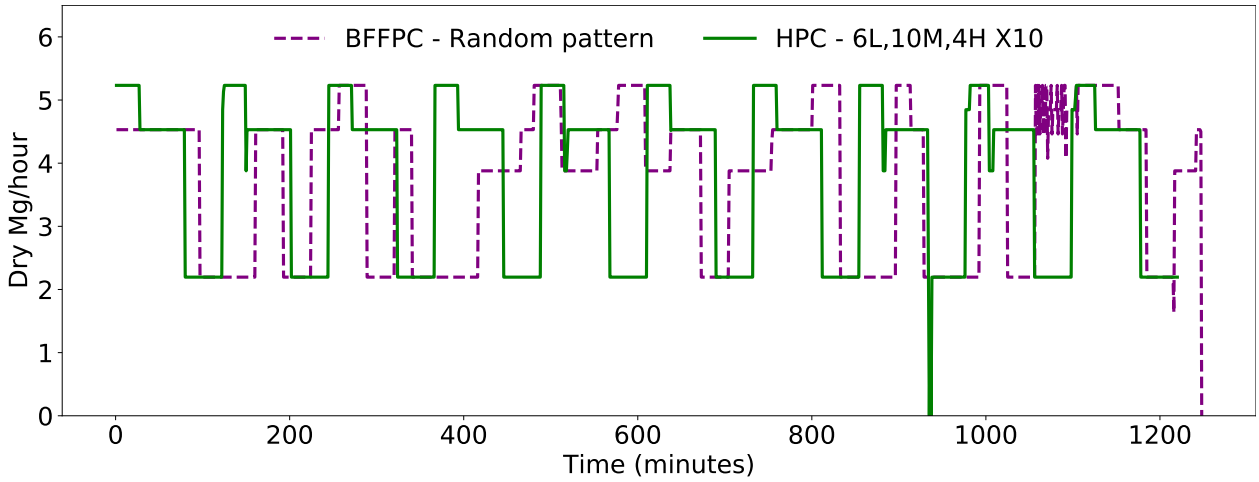
(b) With fractional milling

Figure 2: Optimal trajectories of reactor feeding rates for BFFPC (with feeding pattern of "random pattern") and HPC (with feeding pattern of 6L,10M,4H X10)

Figure 3 compares the trajectories of a systems' in-feed rate. We observe that both BFFPC and HPC adjust bale in-feed rates differently. Although the maximum in-feed rate for both pre-processing systems is the same, the sequences of bale feed are different. HPC's in-feed trajectory has a more consistent pattern (same repeated adjustments). If we compare in-feed rate trajectories with and without fractional milling, it is observed that the range of the in-feed rate lies in an interval of 0 dry Mg/hour and 5 dry Mg/hour without fractional milling, but this range is narrower with fractional milling. For instance, we rarely see in-feed rate drops to 0 dry Mg/hour with fractional milling.



(a) Without fractional milling



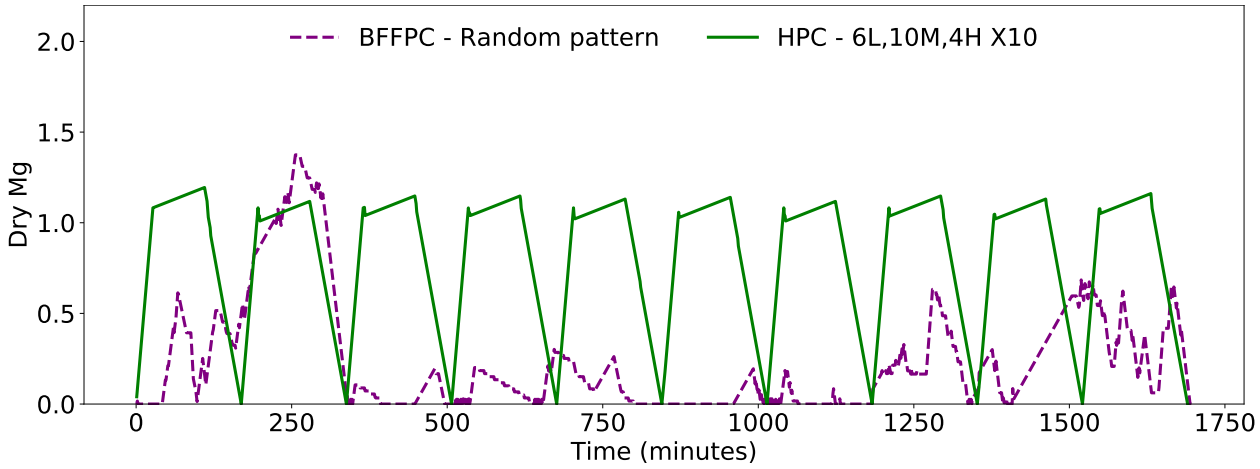
(b) With fractional milling

Figure 3: Optimal trajectories of bale in-feed rates for BFFPC (with feeding pattern of "random pattern") and HPC (with feeding pattern of 6L,10M,4H X10)

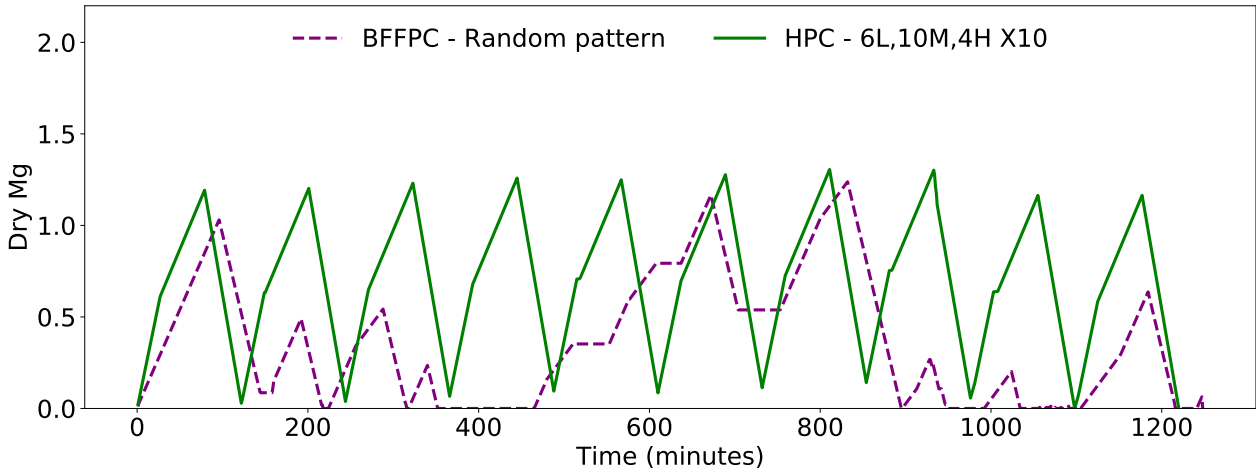
Figure 4 reveals optimal trajectories of the total inventory level in metering and storage bins. We observe that the build up of inventory in storage units for BFFPC is irregular. On the other hand, inventory build up for HPC follows a pattern. Biomass accumulates in storage units while processing low- and medium-moisture bales, and biomass is discharged while processing high-moisture bales. The breakpoints observed for HPC correspond to the times when operators switch between bales with different moisture levels. This approach to inventory control minimizes inventory level. The results of Figure 4 show that HPC tends to keep more inventory than BFFPC. The higher inventory level leads to a shorter processing

time, as well as continuous and smooth feeding of the reactor.

For the feeding patterns presented in Figure 4, we calculate the total inventory carried over the entire modeling horizon. It is observed that BFFPC with fractional milling keeps more inventory than BFFPC without fractional milling. However, HPC without fractional milling carries more inventory than HPC with fractional milling. We reach the same conclusions when analyzing HPC and BFFPC with other feeding patterns.



(a) Without fractional milling

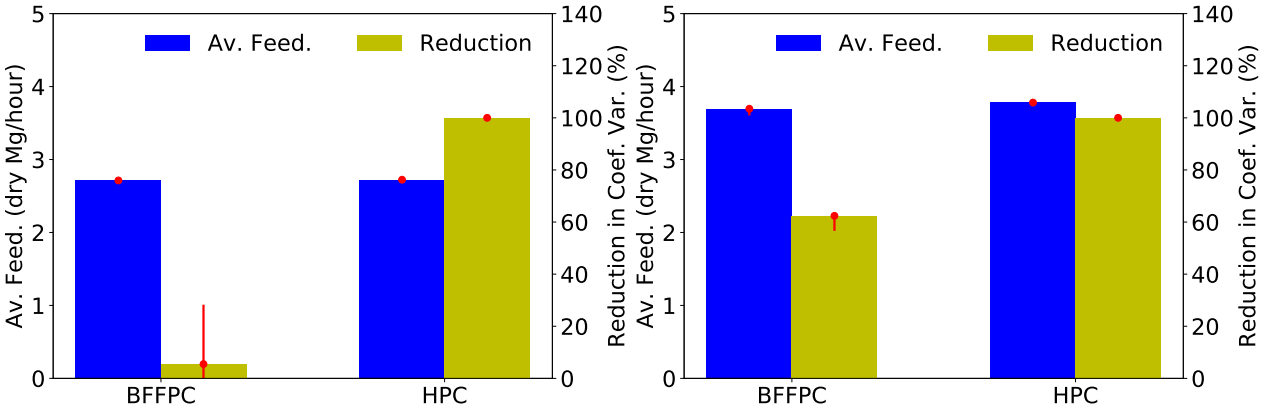


(b) With fractional milling

Figure 4: Optimal trajectories of total inventory in metering and storage bins for BFFPC (with feeding pattern "random pattern") and HPC (with feeding pattern of 6L,10M,4H X10)

Figure 5a shows a reduction in the coefficient of variation from 5.48% to 100% in BFFPC and HPC correspondingly, in a process design without fractional milling. The corresponding

average feeding rates increases from 2.713 dry Mg/hour to 2.723 dry Mg/hour. In the process design with fractional milling, we observe similar improvements in the average feeding rate and variability in feeding of reactor. BFFPC has an average feeding rate of 3.696 dry Mg/hour and HPC 3.780 dry Mg/hour. The reduction in the coefficient of variation in BFFPC and HPC are 62.38% and 100%, respectively (Figure 5b).



(a) Without fractional milling

(b) With fractional milling

Figure 5: Average feeding rate of reactor and reduction in coefficient of variation of reactor feeding rate for BFFPC (with feeding pattern "random pattern") and HPC (with feeding pattern of 6L,10M,4H X10)

4.2. Evaluating the role of buffer size and location on system's performance

The proposed MILP formulation allows capacity expansions of storage units, if economical. By economical, we refer to trade-off between extra operation cost stemming from larger storage capacities and cost saving gained through shorter processing time. Our model chooses to expand storage capacities when the latter is larger than the former. In addition to the metering bin, we add a storage bin with capacity 5 dry Mg between pelleting and the reactor. We experiment with different feeding patterns and allow the model to expand storage capacity if needed. In Figures 6 to 8, "optimized buffer size capacity" refers to the model that allows expansion of the capacity of storage units when needed, and "fixed capacity" refers to the model that does not allow the expansion of the capacity of storage units. In these experiments we assume that the system operates under HPC.

Figure 6 presents the maximum inventory of the metering bin and storage bin, and the average feeding of the reactor for different feeding patterns. These results show that the average feeding of the reactor is highest for the Baseline pattern. The inventory level for

the Baseline pattern is low and does not reach the maximum storage capacity since the moisture level of bales changes frequently. Thus, the system does not inventory in large amounts. Inventory is lowest for patterns that begin by processing every high moisture bales (40H,60L,100M and 40H,100M,60L). Since low moisture bales are processed after the high moisture bales, there is no need to carry inventory. However, these patterns have the lowest feeding of the reactor.

Based on our experiments, the storage bin between pelleting and the reactor is utilized more than the metering bin. The inventory of storage bin enables continuous flow of biomass to the reactor. The capacity of the storage bin impacts the performance of the system when processing patterns 60L,100M,40H and 100M,60L,40H. Doubling the storage bin capacity increases the average feeding of the reactor by 81.5 Kg/hour.

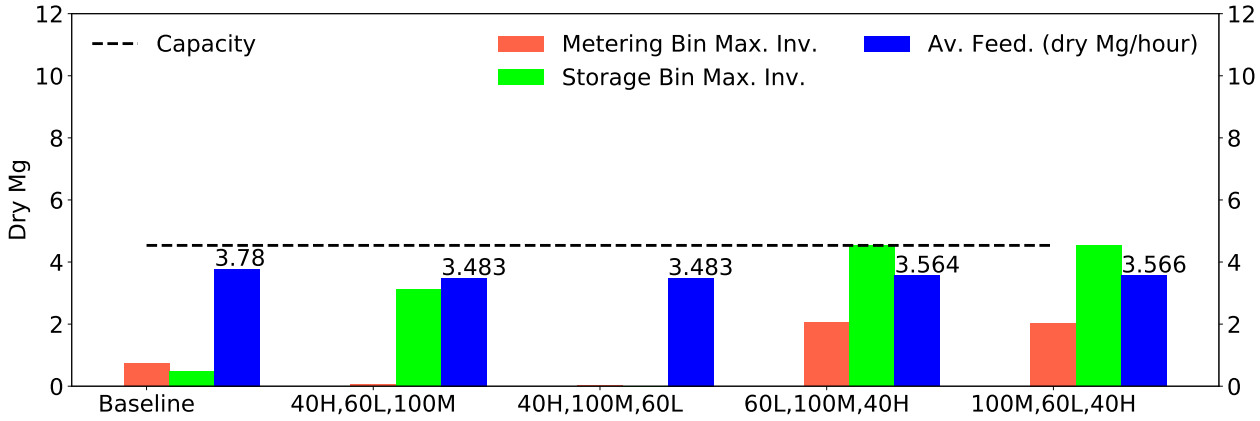
We conduct additional experiments with the baseline pattern and summarize the results in Figures 7 and 8. The results show that the system without fractional milling does not need expansion in storage units. In an optimal solution of the system with fractional milling, buffer size capacities are expanded by 100%.

The results of Figures 7b and Figure 8b show that the HPC system improves its performance when additional storage capacity is available. In this case, the process throughput is 3.649 dry Mg/hour, the reduction in the coefficient of variation is 100%, the average unit cost is $37.15/dry Mg, and the processing time is 21.07 hours. If the existing storage capacity (of 4.54 dry Mg and 24.07 cubic meter) in the process design did not increase, the average throughput would be lower (3.564 dry Mg/hour), the reduction in coefficient of variation would be lower (83.06%), the average unit cost would be lower ($35.97/dry Mg), and the process time would be higher (21.57 hours). The increase of unit cost is due to the investment cost needed to expand the storage capacity.

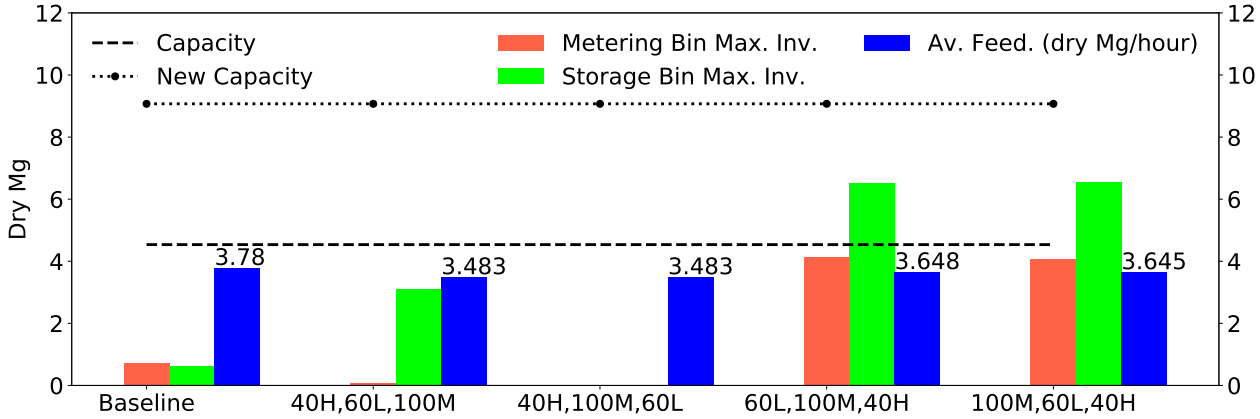
These additional costs outweigh the reductions of processing costs due to shorter processing times.

4.3. Cost of operating the system

Table 2 summarizes the results of the sensitivity analysis of BFFPC and HPC. We present cost, processing time, average (Avg. Inv. in the table) and maximum inventory, average



(a) Fixed capacity

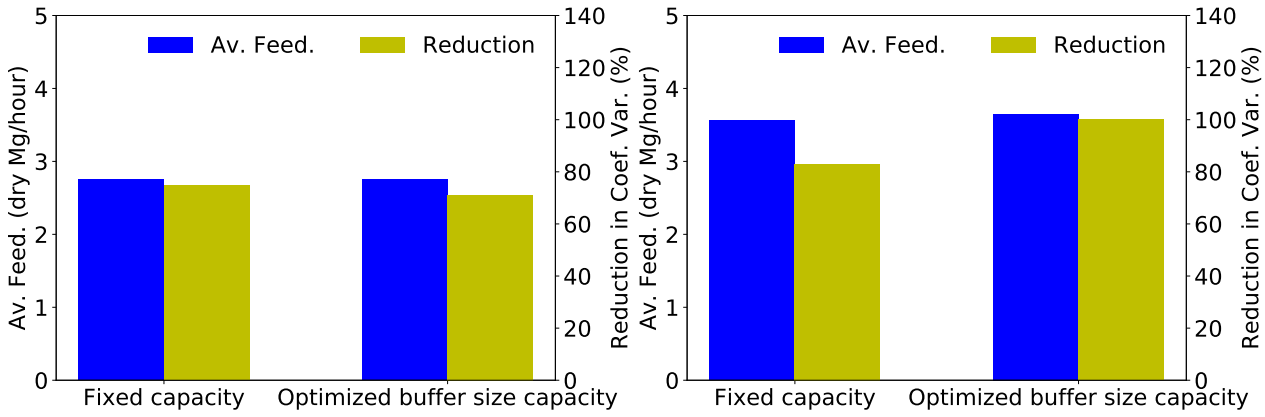


(b) Optimized buffer size capacity

Figure 6: Evaluating the impact of buffer size and location on the performance of HPC

feeding of the reactor and the coefficient of variations for different bale feeding patterns. For BFFPC, we randomly select six different patterns (shown as Rnd. # in the table). The baseline pattern for HPC gives the lowest cost ($33.94/dry Mg), the lowest processing time (20.33 minutes), the highest feeding of the reactor (3.78 dry Mg/hour) and the lowest coefficient of variation of the reactor feeding rate (0.00).. Results reported in Table 2 pertains to the system design with fractional milling.

Similar to Table 2, it might be useful to show the sensitivity results with respect to pre-processing system designs with and without fractional milling. Table 3 presents the costs and the minimum processing time for BFFPC and HPC. In this table, we prefer to show only Rnd. 6 for BFFPC and baseline pattern for HPC as these patterns proven to be more superior over other patterns utilized within BFFPC and HPC. We observe that



(a) Without fractional milling

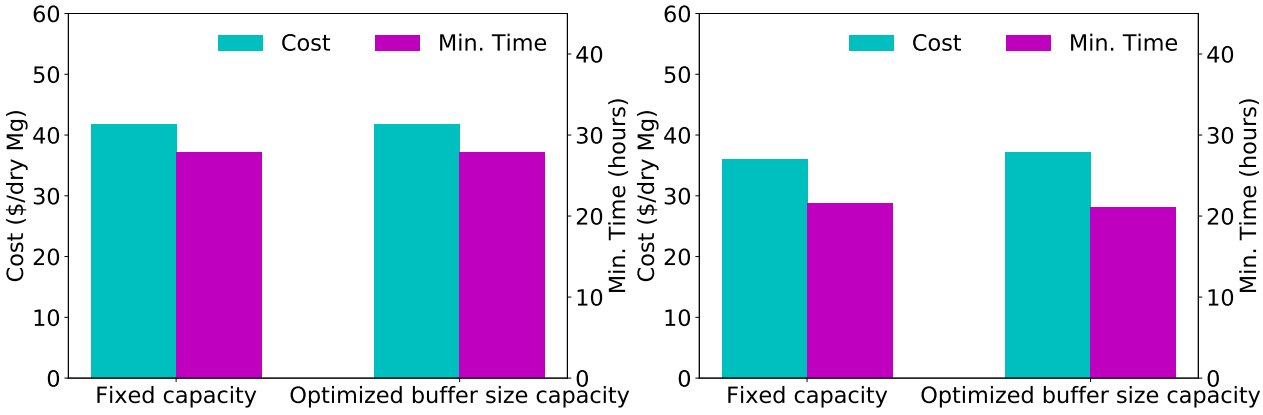
(b) With fractional milling

Figure 7: Average feeding rate of reactor and coefficient of variation in reactor feeding rate with fixed and optimized capacities of storage units

HPC reduces costs by 0.36% and reduces processing time by 0.35% over BFFPC in a process without fractional milling. When fractional milling is utilized, HPC reduces costs by 2.22% and reduces processing time by 2.24%. These results also indicate improvements of processing time and costs due to fractional milling.

Control	Feeding Patterns	Cost ($/dry Mg)	Min. Time (hours)	Avg. Inv. (dry Mg)	Max. Inv. (dry Mg)	Av. Feed. (dry Mg/hour)	Coef. Var.
BFFPC	Rnd. 1	34.71	20.80	0.28	1.07	3.70	0.21
	Rnd. 2	34.70	20.80	0.39	1.13	3.70	0.24
	Rnd. 3	34.71	20.80	0.36	1.26	3.70	0.21
	Rnd. 4	35.58	21.33	0.33	1.45	3.60	0.25
	Rnd. 5	35.59	21.33	0.12	0.67	3.60	0.25
	Rnd. 6	34.71	20.80	0.36	1.24	3.70	0.21
HPC	60L,100M,40H	37.15	21.07	5.91	10.66	3.65	0.00
	100M,60L,40H	37.17	21.08	3.92	10.64	3.65	0.00
	40H,60L,100M	36.80	22.07	1.05	3.18	3.48	0.26
	40H,100M,60L	36.80	22.07	0.00	0.02	3.48	0.28
	Baseline	**33.94**	**20.33**	**0.71**	**1.33**	**3.78**	**0.00**

Table 2: Results of the sensitivity analysis



(a) Without fractional milling

(b) With fractional milling

Figure 8: Cost of operating system and minimum time to process all bales with fixed and optimized capacities of storage units

Pre-processing System Design	**Control**	**Cost ($/dry Mg)**	**Min. Time (hours)**
Without fractional milling	BFFPC	42.32	28.27
	HPC	42.16	28.17
With fractional milling	BFFPC	34.71	20.80
	HPC	33.94	20.33

Table 3: Cost of operating the system and minimum time to process 200 bales for BFFPC (with feeding pattern "random pattern") and HPC (with feeding pattern of 6L,10M,4H X10)

4.4. Summary of Experimental Results

We conducted a thorough and novel analysis of biomass processing systems using technical process data collected via a diverse set of experiments conducted at INL's PDU. We also assembled techno-economic data by running BLM, which performed several simulation runs. The results of these experiments lead to a number of observations, which we believe are useful to practitioners.

Observation 1: Feeding bales in a system following patterns based on moisture level, which repeat frequently and begin by processing biomass of low moisture level (i.e., baseline pattern), reduces operating costs, processing time, and average and maximum inventory levels; and increases the feeding rate of the reactor; as well as maintains a continuous flow of biomass to the reactor (see Table 2).

Observation 2: A system that uses HPC (rather than BFFPC) increases utilization of the reactor and reduces investment costs by minimizing variations in the feeding of a reactor. For example, our experiments show that a reactor that processes 3 dry Mg/hour in a system that uses HPC (without fractional milling) could process on the average the same amount of biomass per hour as a reactor that processes 5 dry Mg/hour in a system that uses BFFPC (see Figure 2a).

Observation 3: Storage space requirements are similar in systems that utilize HPC (baseline pattern) and BFFPC. However, inventory level is higher in systems that use HPC. Such a system maintains a larger inventory to ensure a continuous flow of biomass to the reactor.

Observation 4: Locating a storage space next to the reactor is an effective strategy to maintaining a continuous flow of biomass to the reactor.

Observation 5: Use of fractional milling reduces operating costs and increases processing time.

4.5. Validation of Modeling Results

In an effort to validate the model results, we conducted a small size real experiment by using INL PDU's equipment. We processed 20 3-pass corn stover bales by using two-stage grinding structure.

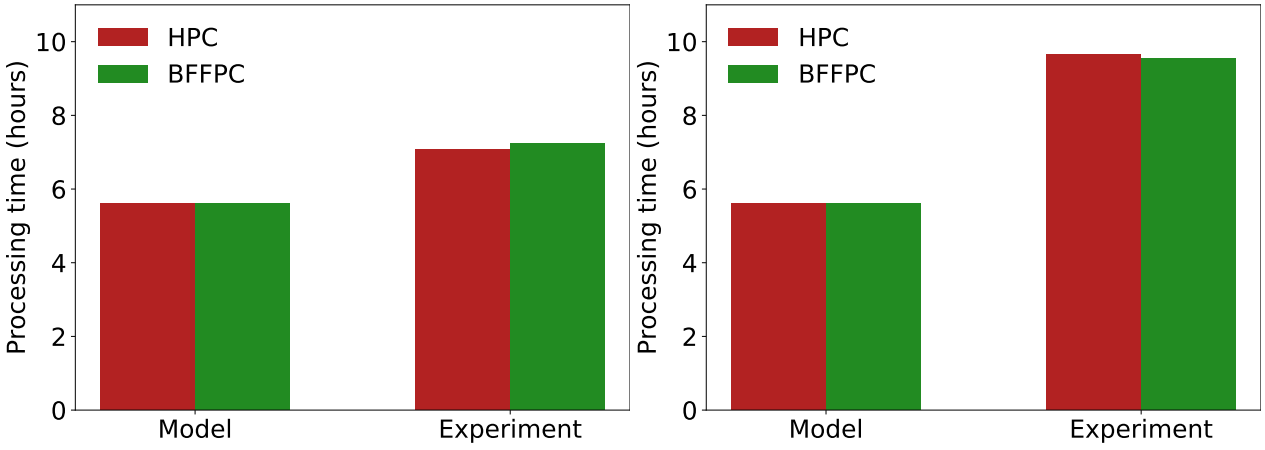
For the sake of making a comparison between the model and the experiment results, we used a constant composition of bales consisting of the same number of low-, medium-, and high-moisture bales. We created feeding patterns for HPC and BFFPC. Table 4 demonstrates the control approaches, composition of bales, and feeding patterns used.

Composition of Bales	**Control**	**Feeding Pattern**
5L,10M,5H	HPC	1L,2M,1H X5
	BFFPC	4M,1L,2M,2L,1H,1L,1H,2M,3H,1L,2M

Table 4: Experiment set-up for 3-pass corn stover

We evaluate and compare the model and the experiment results based on processing time and the variation in reactor feeding rate. Figures 9a and 9b illustrate actual and total

processing time, respectively. Total processing time in this context refers to actual processing time plus down time. Since the mathematical models do not account for any down time, total and actual processing times are identical.



(a) Actual processing time

(b) Total processing time

Figure 9: Processing times for HPC and BFFPC

We infer from Figures 9a and 9b that actual and total processing times computed by the mathematical models are equivalent irrespective of control approaches used. However, in Figure 9a, we observe in experiments that actual processing time of HPC is slighly shorter than that of BFFPC. In contrast, Figure 9b reveals that total processing time of HPC is slightly longer than that of BFFPC. Down time was longer while processing the bales with HPC, which clarifies the reason why total processing time of HPC is longer even though its actual processing time was shorter in comparison to BFFPC's times. Down time during HPC processing was longer because HPC was performed prior to BFFPC, and operators were less experienced about processing bales in avoiding equipment clogging and failures.

Figure 10 illustrates the reduction in coefficient of variation of reactor feeding rate in the case that HPC is used. In this analysis, we are solely interested in HPC because our experience shows that HPC is much more effective in reducing coefficient of variation when compared to BFFPC. Hence, the question remains as to whether the reduction amount obtained with mathematical models can be achieved with experiments.

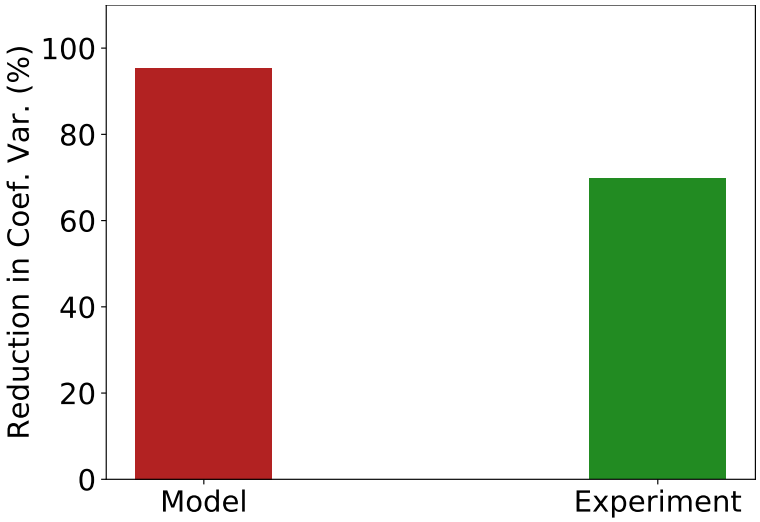


Figure 10: Reduction in coefficient of variation

According to Figure 10, reduction in cofficient of variation obtained with mathematical models can not be fully achieved in practice.

We show more details about this validation experiments in the supplementary material.

5. Discussion

The reliability of the model and its output depends on input data, assumed stochasticity of the model input data, repeatability of modeling results, and obtaining consistent managerial insights under different modeling scenarios. Since model input data are deterministic, the model results in the same optimal solutions every time when it is solved. Hence, model output is repeatable for the same input data. Moreover, we had tested different models with alternative forms of objective function and constraints. Those forms include various structures of minimization of processing times, integrating particle size distributions, and capturing of volume change in storage units with non-linear constraints. We observed that these models result in approximately the same managerial insights. Hence, it is expected that the model would produce reliable insights on optimal process control and bale sequencing in a biomass pre-processing system.

The model can be used to identify a process control when the system processes feedstocks with different characteristics via adding constraints or sensitivity analysis. For example, biomass particles vary by size and shape. If relationship between particle size distribution

(i.e, 10^{th}, median, and 90^{th} percentile) and equipment in-feed rate is known, additional constraints can be added to the model to capture the relationship between the control variables and the feedstock particle size variation. This constraint allows to control the particle size variability in the process. Large-scale, practical implementation of the proposed process control, HPC, is challenging since it requires a standardized bale format, automatic handling (sorting) of a large number of bales, real-time monitoring of biomass attributes, and automated process control. Nevertheless, these technologies exist and are currently being used by the European bioenergy and agricultural sectors. For example, Ali et al. [42] presents the design for a low cost miniaturized chipless RFID tag for short-range biomass tracking and monitoring. An article published in ArgiTech Tomorrow [43] describes the use of RFIDs in the agricultural system to capture and store the date of harvest, the field where it was harvested, the temperature, weight, moisture level, and the nutritional information. PROCESSBIO [44], a Danish company, manufactures an equipment that reads RFID cards in incoming bales. PROCESSBIO also manufactures conveyors and robotic cranes that can handle up to 105 bales per hour. These material handling equipment are currently used by Sleaford Renewable Power Plant in United Kingdom [45]. QUBIQA [46] is another European company, located in Denmark and Poland, that produces equipment for automated material handling and automated process control. These equipment are currently being used by BWSC Biomass Renewable Energy Plant in United Kingdom [47].

Future research will focus on integrating the outcomes of Discrete Element Method (DEM) models with optimization models. DEM models are typically used to simulate the mechanical and flow behavior of feedstocks in equipment for given feedstock characteristics and equipment design. The results from these simulations can be used to develop functional relationships between feedstock characteristics (e.g., type, moisture content, particle size distribution, density), equipment setting, and biomass flow. These functional relationships can be incorporated into the optimization model to control the flow of biomass to the reactor. For example, biomass type, moisture level and mill speed in the grinders impact biomass density. The density of biomass impacts its volume, and as a consequence, the storage capacity of the metering bin. Thus, outcomes of DEM models can be used to develop functional relationships between biomass type, biomass moisture level, mill speed in grinders and den-

sity to be included in optimization. There are a few DEM models for biomass feedstocks, such as, Guo et al. [48], which focuses on switchgrass and Xia et al. [49], which focuses on pinewood. We will incorporate the outcomes of similar models to optimization to improve the accuracy of our results.

6. Conclusions

Variations in feedstock characteristics, such as feedstock moisture and density, lead to an inconsistent flow of feedstock from the biomass pre-processing system to a rector in-feed system. In this research, we developed an optimal process control method for a biomass pre-processing system comprised of milling and densification operations to provide consistent flow of feedstock to a reactor's throat. Our case study based on switchgrass with moisture level ranging from 10 to 25%, finds that the proposed optimal process control: (i) reduces the variation of a reactor's feeding rate by up to 100%; (ii) reduces the cost of operating the system by 0.36% to 2.22%; and (iii) reduces processing time by 0.35% to 2.24%. This performance is possible via the identification of optimal bale sequencing, equipment in-feed rate in the process, and process buffer location and size in the biomass pre-processing system. A biorefinery can adapt proposed control to achieve its design capacity.

This modeling results provided a number of managerial insights that can be utilized during practical operation of feedstock pre-processing systems. For example, sequencing bales based on moisture in a large-scale commercial biorefinery creates the opportunity to maintain a continuous flow of biomass to the reactor. In addition, locating storage space next to the reactor is an effective strategy to maintaining a continuous flow of biomass to the reactor viable, but it may bring about additional costs of equipment, and space. The trade-off between storage space and location and cost depends on feedstock variation and equipment in the biomass pre-processing systems. The proposed mixed-integer linear optimization model described in this paper can be utilized to determine the optimal storage space.

7. Credit author statement

Fikri Kucuksayacigil: Development and implementation of the model utilizing CPLEX/Gurobi, preparing results, writing original draft. Mohammad Roni: Conceptualization, development of the methodology, scoping the study, data collection, writing, preparing the final manuscript. Sandra D. Eksioglu: Development of the methodology, supervision, writing, review and editing. Tanveer H. Bhuiyan:Wrote model validation section. Qiushi Chen: Writing, review, and editing.

8. Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

9. Acknowledgment

The funding of this work was provided by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Bioenergy Technologies Office under award Number DE-EE0008255 and Department of Energy Idaho Operations Office Contract No. DE-AC07-05ID14517. The authors greatly thank INL staff in the DOE Biomass Feedstock National User Facility for providing technical data for this study. Specifically, we acknowledge Neal A. Yancey and Jaya S. Tumuluru, who are the individual INL contributors to this research and provided helpful comments, data, and other forms of support for this analysis. The views expressed herein are those of the author only, and do not necessarily represent the views of DOE or the U.S. Government.

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