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Bi-objective optimization of forest-based biomass supply chains for minimization of costs and deviations from safety stock

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A B S T R A C T

Bioenergy from forest-based biomass could reduce fossil fuel dependency, GHG emissions, and generated wastes. However, the inherent complexity, uncertainty, and high cost of forest-based biomass supply chains could hinder the economic viability of bioenergy projects. The supply chain activities including transportation, storage, handling, and preprocessing of biomass are interdependent and require proper planning. Therefore, in previous studies, mathematical programming models were developed to plan and optimize the biomass supply chain activities. In this paper, a bi-objective optimization model is developed for tactical planning of the forest-based biomass supply chains in order to determine the trade-offs between the total costs and the possible deviations from the safety stock. The first objective is to minimize the upstream supply chain costs, and the second objective is to minimize the negative deviations of monthly inventory from the safety stock. The decision variables include the optimal monthly biomass flows, preprocessing, and inventory levels. The model is applied to the case of a biomass gasification at a Kraft pulp mill in British Columbia, Canada. The output of the model is a set of Pareto optimal solutions, which shows the trade-offs between the objectives of cost and safety stock deviation. This approach has the potential to assist the decision makers by providing a set of solutions to opt from based on their preferences and their attitude towards supply disruption risk. The results indicate a maximum of 18% cost savings is possible if the inventory level deviates from the safety stock. A sensitivity analysis is also performed to assess the impact of variations in the biomass availability and cost, and feedstock demand on the Pareto optimal solutions. According to the sensitivity results, feedstock demand is the most sensitive parameter.

Introduction

Forest-based biomass including harvesting and mill residues have become a popular sustainable source of renewable energy around the world [33]. It can be transformed into heat, electricity, and biofuels [37]. Its conversion into bioenergy could provide economic and environmental benefits compared to its burning or disposal in the landfills [33]. In addition, its utilization to produce bioenergy could increase energy security by replacing fossil fuels [33], and could contribute to job creation and local development especially in rural areas [17].

Despite many advantages, there are several challenges related to forest-based biomass utilization for bioenergy/biofuel production. In addition to technology and production challenges, characteristics of forest-based biomass result in having a high cost and complex supply chain. Bulkiness, low energy content, and scattered availability of forest-based biomass lead to high transportation costs [5,17]. Additionally, forest-based biomass procured from different supply sources has different characteristics. Thus, it may need multiple preprocessing steps to have a uniform and acceptable feedstock for the intended conversion technology.

Another challenge is the temporal variation in the availability of forest-based biomass. Forest-based biomass is a by-product of processing mills and harvesting activities. Its availability varies by the demand for other forest products and also seasonal accessibility to forest roads and collection areas [7]. To ensure a constant supply of feedstock to the conversion plant, storage of forest-based biomass in seasons of abundance may be required. In addition, a safety stock is usually added to the inventory to secure the operability of conversion process in case of biomass supply disruptions [42]. This increases the storage and handling costs [5].

Supply chain activities of forest-based biomass including collection, transportation, preprocessing and storage are interdependent and

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complex processes. These activities contribute to the cost of delivered forest-based biomass, which accounts for up to 50% of the total cost of produced biofuel/bioenergy [15,27]. The high cost of delivered forest-based biomass can hinder the economic viability of the bioenergy projects [17,30,49], therefore, proper planning of supply chain activities at strategic, tactical, and operational levels is required and has been the focus of many previous studies.

In the present study, the mentioned upstream supply chain activities, i.e., transportation, preprocessing, and storage, at tactical level are optimized for the production of syngas from forest-based biomass using a gasification technology. The goal of this study is to minimize the delivered cost of forest-based biomass and determine the potential cost savings by allowing flexibility in the monthly safety stock level. To model this flexibility, the monthly inventory of biomass is allowed to negatively deviate from the safety stock and the negative deviations are minimized in addition to minimizing the total costs.

Strategic planning of biomass gasification at different facilities including pulp mills were optimized in previous studies [15,16,48,47,50,52]. Decisions in the strategic optimization studies included determining the technology investments, pathways, capacities, locations, and long-term flow of biomass and bioproducts. To the best of our knowledge, no previous study optimized the tactical planning of biomass supply chains for gasification. Nonetheless, optimization of tactical planning of upstream supply chains has been conducted in the literature for the production of heat [6], power [28,44,46], and biofuels [55,56] from forest-based biomass. Monthly biomass flow and inventory decisions were optimized in all of the reviewed papers. In addition to the mentioned tactical decisions, the models in [44] and [56] included the long-term decisions of facility location and/or capacity determination.

In previous papers, the inventory of biomass was formulated and modeled according to the problem specifications and needs. In most of the reviewed studies [6,8,44,46,55,56], the inventory level was strictly capped by the maximum storage capacity. Models in [28,44,46] included a storage upper limit that the inventory level could exceed at a penalty cost. [46] and [44] assumed that the quality and heating value of biomass would decrease at a rate if the inventory level dropped below a lower level. Among the reviewed literature, models in [6,44] considered the safety stock and did not allow the inventory to drop below the safety stock level.

From a practical point of view, keeping a safety stock is a strict constraint. Although this amount can help to reduce the risks associated with the supply and demand uncertainties, it has a cost, e.g., purchase, handling, and dry matter loss during storage [45]. According to supply managers, the purpose of keeping inventory is to provide some buffer for the biomass supply and demand mismatch rather than keeping it for the sake of inventory at all costs. The inventory level is allowed to go slightly under the specified level, if the demand is met and it reduces the total supply chain costs. In other words, the purpose should be to keep a safety stock that is as close as possible to a desired level, while allowing some negative deviations from this level when cost savings are possible. Therefore, in this paper, we take a different approach from previous studies to address the problem at hand and allow negative deviations from the safety stock. A bi-objective optimization is developed in this paper to minimize those deviations as a separate objective function, in addition to minimizing the total supply chain costs. The aim of our approach is to preserve the nature of inventory deviation values and to avoid translating them into costs in order to depict the possible savings in the supply chain cost resulted from deviations in the safety stock level.

In problems with multiple objectives of different natures, decision makers prefer to have a set of optimal solutions rather than a single solution. This provides them with a clear picture about the trade-off between the objectives [26], which is very helpful in decision making as managers consider the cost as well as other experience-driven, qualitative, and non-technical factors in their decision making [19]. In such situations, if a set of optimal solutions is provided, the decision maker will be able to compare and decide among the solutions based on their preferences [19]. Therefore, in this study, the bi-objective optimization model is solved using the Augmented Epsilon Constraint (AUGMECON) method to provide a set of optimal solutions for tactical planning of the biomass gasification supply chain. The first objective of the model minimizes the upstream supply chain costs, and the second objective minimizes the negative deviations from the safety stock level. The set of optimal solutions indicate the trade-off between supply chain costs and negative deviations from the safety stock. The model is applied to the case of a large pulp mill in British Columbia (BC), Canada. At the pulp mill, biomass including harvesting and sawmill residues are planned to be fed to a gasifier to produce syngas in order to cover the heat demand of the lime kiln burner. The developed model is a Mixed Integer Programming (MIP) model and determines whether the establishment of a terminal storage is economical and needed. It also prescribes: (1) the optimum monthly flow of each type of residues from supply sources to a potential terminal storage and the mill, (2) the optimum monthly inventory level of each type of residues at each of the two facilities, and (3) the optimum monthly amount of residues to be preprocessed and fed to the gasifier. The sensitivity of the Pareto optimal solutions to the changes in the input parameters are also investigated in this paper.

Case study

Since 2000s, the pulp and paper sector in BC has been challenged by a major decrease in the pulp demand. This was due to the shift from paper-based communication to digital media; rise of new competitors in the US and Europe; and new environmental policies promoting reduce, reuse, and recycle of paper [14]. These challenges followed by the industry transformations provided the pulp and paper mills with potential opportunities to generate new streams of revenue [20]. One transformation strategy in response to the challenges has been the production of bioenergy and bioproducts [34]. Many pulp mills have been able to use forest-based biomass, hereinafter referred to as biomass, in their auxiliary boiler to generate bioenergy, namely, heat and power. This has helped mills to increase their energy efficiency and sell their excess energy to the utility company BC Hydro, under Energy Purchase Agreements (EPAs) [18,20].

However, in February 2019, BC Hydro announced their plans for reduced energy purchases in the future due to surplus of electricity that they expected to have through 2030s. Consequently, no more EPAs would be awarded and EPAs with bioenergy generating facilities including pulp mills would not be renewed [22].

At the same time, in 2019, the CleanBC program provided potential opportunities for pulp mills through gasification of their otherwise wasted biomass [36]. Gasification is a thermochemical process to convert stored chemical energy in biomass feedstock with a low moisture content (<50%) to a combustible gas mixture (i.e., raw syngas) [32]. The generated syngas could replace the natural gas to fuel the lime kiln in pulp mills. In addition, it can be further processed and sold to FortisBC as Renewable Natural Gas (RNG) or could be used as biofuel for transportation [36]. This facilitates meeting the requirements set by the CleanBC program, which is to supply at least 15% of industrial and residential natural gas demand from renewable sources by 2030 [36]. This translates into introducing a new product line in pulp mills that could potentially bring in more revenue and sustainability to the BC Forest Sector.

We study the case of a large Kraft pulp mill in BC. In addition to pulp production, the mill has been producing electrical power and selling the surplus to BC Hydro under an EPA [12]. The pulp mill owns a chemical recovery line to recycle black liquor produced within the Kraft pulping process. This line includes a recovery boiler, an evaporation plant, and a lime kiln. The heat demand of the lime kiln, which is approximately one million GJ per year, is currently met by burning natural gas. Lime kilns consume the largest portion of the fuel in modern Kraft pulp mills [51]. Therefore, replacing the natural gas consumed in the lime kiln with renewable energy could benefit the mill by reducing fuel costs as well as lowering GHG emissions [36,51].

Since the cancellation of EPAs by BC Hydro, the mill has been looking into installing a gasifier at the mill using the available government incentives. Biomass is planned to be fed to the gasifier and generated syngas is bound to replace the natural gas consumed in the lime kiln.

A schematic representation of the mill's biomass gasification supply chain is presented in Fig. 1. As it can be seen in the figure, the supply chain of this problem starts from supply nodes and ends at the gasifier installed at the mill. Biomass could be supplied from 505 forest cut blocks and five sawmills. In some months, the amount of biomass available at an economic delivered cost, may become lower than the demand level. This could be due to variations in the gasifier's feedstock demand and/or availability of biomass. Therefore, biomass storage might be needed to economically match the demand and supply. Moreover, to prevent any disruptions in the operation of the gasifier, keeping a safety stock of 30 days of gasifier's feedstock demand was recommended by the managers. To store the residues, the pulp mill has an internal open pile storage. However, in case of limited storage space at the plant location, the residues could be stored at a potential terminal storage, alternatively. The terminal storage is assumed to be open pile and located within a 15 km radius.

Residues could be transported directly to the mill or indirectly via the potential terminal storage. Self-unloading trucks are assumed to be used for transportation. Upon arrival at either facility, residues would be unloaded and moved to the storage piles using front-end loaders. At both facilities, front-end loaders are used for pile management during storage. Residues stored at the terminal storage would, then, be sent to the mill when demanded.

At the mill, residues would be reclaimed from the piles using an underground screw reclaimer upon demand. Harvesting residues would directly be sent to the gasifier for drying and gasification. The intended gasifier technology has an inbuilt dryer that reduces the moisture content of residues to its desired level. Sawmill residues, on the other hand, would first be sent to the screener and then drop feed hog for comminution. This is because sawmill residues are not received in a uniform size that is compatible with the gasifier technology. Harvesting residues, on the contrary, would be ground to truck by a mobile grinder at forest roadsides to improve the transportation efficiency [13]. Since it is assumed that they could be ground to gasifier's specification, they would not require further comminution at the pulp mill.

Mathematical formulation

Notations of the developed bi-objective model are presented in Table 1. The model is developed in a generic form that includes multiple terminal storages and gasifier plants.

Objective functions

The first objective function is to minimize the total supply chain costs. It is the summation of all cost components and can be written as Eq. (1).

$$MinimizeZ_1 = CF + CD + CT + CH + CP \tag{1}$$

where CF is the annualized fixed cost of establishing terminal storage(s) (see Eq. (3)), CD is the cost of purchasing, loading, unloading, and transporting of residues from supply sources to terminal storage(s) and plant(s) (see Eq. (4)), CT is the cost of loading, unloading, and transporting of residues from terminal storage(s) to the plant(s) (see Eq. (5)), CH is the cost of residue handling at terminal storage(s) and plant(s) (see Eq. (6)), and CP is the cost of preprocessing at plant(s) (see Eq. (7)).

The second objective function (Eq. (2)) is to minimize the maximum of monthly negative deviations from the safety stock level. Monthly negative deviations for each gasifier (k) are modeled by non-negative slack variables (s_{kt}), which are shown in Eq. (18).

$$MinimizeZ_2 = \sum_k \max_{(t)}(s_{kt}) \tag{2}$$

The bi-objective model could be reduced to a single objective for cost minimization, by eliminating Eq. (2) and setting the slack variables (s_{kt}) to zero.

$$CF = \sum_j \theta_j \times r_j \tag{3}$$

$$CD = \sum_t \Big[\sum_i \sum_k \alpha_{ik} \times (xs_{ikt} + xh_{ikt}) + \sum_i \sum_j \beta_{ij} \times (ys_{ijt} + yh_{ijt})\Big] \tag{4}$$

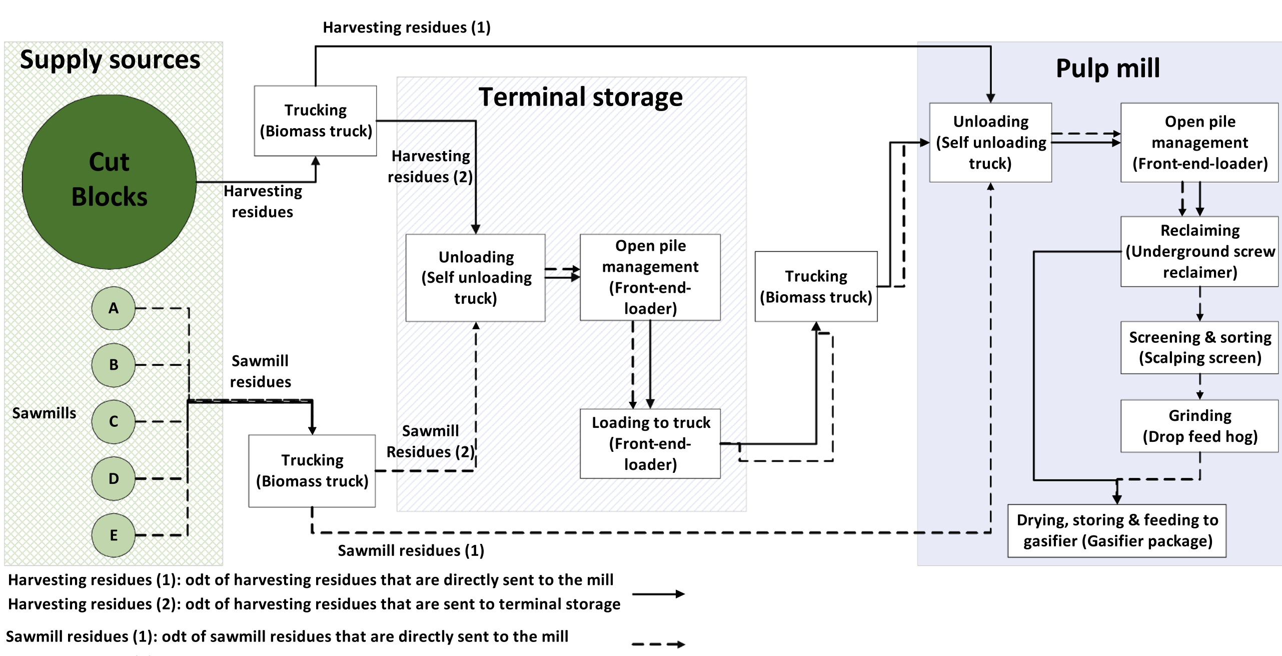

Fig. 1. Supply chain of forest-based biomass gasification at the pulp mill.

Table 1
Indices, decision variables, and parameters of the bi-objective optimization model.

Sets	
$i \in I$	Set of supply sources including sawmills and forest cut blocks
$j \in J$	Set of terminal storages
$k \in K$	Set of gasifier plants
$t \in T$	Set of time periods
Decision variables	
xs_{ikt}	Flow (odt) of sawmill residues from supply source i to gasifier plant k at time t
xh_{ikt}	Flow (odt) of harvesting residues from supply source i to gasifier plant k at time t
ys_{ijt}	Flow (odt) of sawmill residues from supply source $i$to terminal storage j at time t
yh_{ijt}	Flow (odt) of harvesting residues from supply source i to terminal storage j at time t
zs_{jkt}	Flow (odt) of sawmill residues from terminal storage j to gasifier plant k at time t
zh_{jkt}	Flow (odt) of harvesting residues from terminal storage j to gasifier plant k at time t
ws_{jt}	Amount (odt) of sawmill residues stored at terminal storage j at time t
wh_{jt}	Amount (odt) of harvesting residues stored at terminal storage j at time t
vs_{kt}	Amount (odt) of sawmill residues stored at gasifier plant k at time t
vh_{kt}	Amount (odt) of harvesting residues stored at gasifier plant k at time t
us_{kt}	Amount (odt) of sawmill residues ground, dried, and fed to the gasifier k at time t
uh_{kt}	Amount (odt) of harvesting residues dried and fed to the gasifier k at time t
r_j	Binary variable $= \begin{cases} 1 & \text{iftreminalstorage}j\text{isestablished} \\ 0 & \text{otherwise} \end{cases}$
s_{kt}	Slack variable representing the negative deviation (odt) from safety stock level at gasifier plant k at time t
Parameters	
α_{ik}	Unit cost (including purchase, loading, transportation, and unloading) of delivered residues from supply source i to gasifier plant k in \$/odt
β_{ij}	Unit cost (including purchase, loading, transportation, and unloading) of delivered residues from supply source i to terminal storage j in \$/odt
γ_{jk}	Unit transportation cost (including loading and unloading) of residues from terminal storage j to gasifier plant k in \$/odt
σ_j	Unit handling cost of residues at terminal storage j in \$/odt
ρ_k	Unit handling cost of residues at gasifier plant k in \$/odt
μ_k	Cost of screening, reclaiming, and grinding one odt of sawmill residues at gasifier plant k in \$/odt
τ_k	Cost of reclaiming one odt of harvesting residues at gasifier plant k in \$/odt
ε_j^{max}	Maximum storage capacity in odt at terminal storage j
ε_j^{min}	Minimum required inventory in odt at terminal storage j
π_k^{max}	Maximum storage capacity in odt at gasifier plant k
π_k^{min}	Safety stock in odt at gasifier plant k in odt
η_k	Screening and grinding capacity in odt at gasifier plant k
ψ_k	Reclaiming capacity in odt at gasifier plant k
λ_{it}	Maximum availability of sawmill residues in odt at supply source i at time t
ω_{it}	Maximum availability of harvesting residues in odt at supply source i at time t
δ_{kt}	Feedstock demand of the gasifier plant k in odt at time t
θ_j	Annualized investment cost of establishing the terminal storage j
M	A very large number used in the accessory constraint(s) for establishment of terminal storage(s)
L	Dry matter loss (%) per period during storage at terminal storage(s) and gasifier plant(s)

$$CT = \sum_t \sum_j \sum_k \gamma_{jk} \times (zs_{jkt} + zh_{jkt}) \tag{5}$$

$$CH = \sum_t \Big[\sum_i \sum_j \sigma_j \times (ys_{ijt} + yh_{ijt}) + \sum_j \sum_k \rho_k \times (zs_{jkt} + zh_{jkt}) + \sum_i \sum_k \rho_k \times (xs_{ikt} + xh_{ikt})\Big] \tag{6}$$

$$CP = \sum_t \sum_k (\mu_k \times us_{kt} + \tau_k \times uh_{kt}) \tag{7}$$

Constraints

In this section, constraints of the model are explained and represented by Eqs. (8) to (20).

Availability of sawmill residues

Each month, the total amount of residues sent to gasifier plant(s) and terminal storage(s) from each sawmill should be less than or equal to the maximum availability of residues at that sawmill.

$$\sum_j ys_{ijt} + \sum_k xs_{ikt} \le \lambda_{it} \forall i \in I, \forall t \in T \tag{8}$$

Availability of harvesting residues

Each month, the total amount of residues sent to the gasifier plant(s) and terminal storage(s) from each cut block should be less than or equal to the maximum availability of residues at that cut block.

$$\sum_j yh_{ijt} + \sum_k xh_{ikt} \le \omega_{it} \forall i \in I, \forall t \in T \tag{9}$$

Balancing constraint for sawmill residues at gasifier plant(s)

Each month, the total amount of sawmill residues stored at plant(s) is equal to the amount carried over from last month plus any new amount purchased and sent to plant(s), plus any amount received from terminal storage(s), minus the amount that is screened, ground, dried, and fed to the gasifier(s) in that month.

$$vs_{kt} = (1-L) \times vs_{kt-1} + \sum_i xs_{ikt} + \sum_j zs_{jkt} - us_{kt} \forall k \in K, t \in T \tag{10}$$

Balancing constraint for harvesting residues at gasifier plant(s)

Each month, the total amount of harvesting residues stored at plant (s) is equal to the amount carried over from last month plus any new amount purchased and sent to the plant(s), plus any amount received from terminal storage, minus the amount that is dried and fed to the gasifier(s) in that month.

$$vh_{kt} = (1-L) \times vh_{kt-1} + \sum_i xh_{ikt} + \sum_j zh_{jkt} - uh_{kt} \forall k \in K, t \in T \tag{11}$$

Balancing constraint for sawmill residues at terminal storage(s)

Each month, the total amount of sawmill residues stored at the terminal storage(s) is equal to the amount carried over from last month plus any new amount purchased and sent to the terminal storage(s), minus the amount that is sent to the gasifier plant(s).

$$ws_{jt} = (1-L) \times ws_{jt-1} + \sum_i ys_{ijt} - \sum_k zs_{jkt} \forall j \in J, t \in T \tag{12}$$

Balancing constraint for harvesting residues at terminal storage(s)

Each month, the total amount of harvesting residues stored at the terminal storage(s) is equal to the amount carried over from last month plus any new amount purchased and sent to the terminal storage(s), minus the amount that is sent to the gasifier plant(s).

$$wh_{jt} = (1-L) \times wh_{jt-1} + \sum_i yh_{ijt} - \sum_k zh_{jkt} \forall j \in J, t \in T \tag{13}$$

Screening and grinding capacity (minimum of the two)

Each month the amount of sawmill residues that is screened and ground should be less than the maximum monthly operating capacity of screening and grinding equipment pieces.

$$us_{kt} \le \eta_k \forall k \in K, t \in T \tag{14}$$

Reclaiming capacity

Each month, the amount of residues that is reclaimed should be less than the maximum operating capacity of reclaimer equipment at gasifier plant(s).

$$us_{kt} + uh_{kt} \le \psi_k \forall k \in K, t \in T \tag{15}$$

Storage capacity at terminal storage(s)

Each month the amount of sawmill and harvesting residues that are stored at each facility should be between the minimum required inventory and maximum storage capacity of the facility.

$$\varepsilon_j^{min} \times r_j \le ws_{jt} + wh_{jt} \le \varepsilon_j^{max} \times r_j \forall j \in J, t \in T \tag{16}$$

Maximum storage capacity at gasifier plant(s)

Each month the amount of sawmill and harvesting residues that are stored at each facility should be less than or equal to the maximum storage capacity of the facility.

$$vs_{kt} + vh_{kt} \le \pi_k^{max} \forall k \in K, t \in T \tag{17}$$

Safety stock at gasifier plant(s)

Each month the amount of sawmill and harvesting residues that are stored at the gasifier plant can deviate from or equate to the safety stock. In case of negative deviation, the non-negative slack variable (s_{kt}) takes a positive value.

$$vs_{kt} + vh_{kt} + s_{kt} \ge \pi_k^{min} \forall k \in K, t \in T \tag{18}$$

Gasifier feedstock demand

In each month, the amount of sawmill and harvesting residues that are fed to the gasifier should be greater than or equal to the fuel demand of the lime kiln.

$$us_{kt} + uh_{kt} \ge \delta_{kt} \forall k \in K, t \in T \tag{19}$$

Logical (accessory) constraint for establishment of terminal storage (s) that ensures residues are sent to terminal storage only if it is established.

$$\sum_t \sum_i (ys_{ijt} + yh_{ijt}) \le M \times r_j \forall j \in J \tag{20}$$

Sign restriction for decision variables:

$$xs_{ikt}, xh_{ikt}, ys_{ijt}, yh_{ijt}, zs_{jkt}, zh_{jkt}, ws_{jt}, wh_{jt}, vs_{kt}, vh_{kt}, us_{kt}, uh_{kt}, s_{kt} \ge 0 and r_j \in \{1,0\} i \in I, j \in J, k \in K, t \in T$$

Linearization

The second objective of the proposed model is non-linear as it contains a maximum function. Following steps are taken to linearize the objective function:

1) A new auxiliary non-negative variable, $MaxS_k$, is defined which replaces the maximum function and takes the maximum of all s_{kt} values over 12 months (t)s for each k;
2) Eq. (2), the non-linear objective function, is replaced by Eq. (21); and
3) A new constraint as Eq. (22) is added to the model, which ensures that the new variable takes the maximum among all s_{kt} values. In other words, for each gasifier (k), the $MaxS_k$ will be equal to the highest monthly inventory deviation or $\max_{(t)}(s_{kt})$.

$$Minimize Z_2 = \sum_k MaxS_k \tag{21}$$

$$s_{kt} \le MaxS_k \forall k \in K, t \in T \tag{22}$$

Input data and parameters

Biomass availability

The maximum monthly availability of residues at each sawmill and harvesting cut block i is shown by λ_{it} and ω_{it}, respectively, in the model formulation. An annual 81,625 odt of sawmill residues could be procured from five sawmills that are on average 55 km away from the mill. The monthly supply from these sawmills is assumed to be constant throughout the year, except in the months of May, June, July, and August for Sawmills A, B, C, and D, respectively. Their supply is reduced by half in these months due to a two-week maintenance period. Average unit delivery cost of sawmill residues to the pulp mill is $30 per odt. This cost includes purchase, trucking, loading, and unloading costs.

The total annual supply of harvesting residues available to the pulp mill is estimated at 148,988 odt by FPInnovations. This amount is available from 505 cut blocks at the nearby Timber Supply Areas (TSAs). The average distance of these cut blocks to the mill is about 129 km. The average cost of harvesting residues delivered to the mill is $133 per odt. This includes grinding, trucking, loading, unloading, and road maintenance costs.

Availability of harvesting residues at each cut block and in each month is estimated using the average monthly harvest ratios of the related TSAs. These ratios are calculated based on the Harvest Billing System's (HBS) data over five years (2015–2019). The monthly harvest ratios, and consequently the availability of harvesting residues, drop in the months of April, May, and June.

All residues are assumed to have a moisture content of 60% as they are received. They have to be dried to 10% moisture content or less to meet the gasifier's design requirement.

Feedstock demand

The average annual natural gas consumption of the lime kiln burner has been 1,187,974 GJ over seven years. Assuming an 81% biomass to syngas conversion efficiency for gasifier [37] and a Lower Heating Value (LHV) of 18 (MJ kg^{-1}) for the feedstock, the monthly feedstock demand of the gasifier, shown as $\delta_{k=1,t}$ in the model formulation, is calculated using Eq. (23).

$$Feedstock\ demand\ (odt) = \frac{Monthly\ energy\ consumption\ of\ the\ lime\ kiln\ (GJ) \times 1000 \left(\frac{MJ}{GJ}\right)}{Efficiency \times Feedstock\ LHV \left(\frac{MJ}{kg}\right) \times 1000 \left(\frac{kg}{odt}\right)} \tag{23}$$

The annual feedstock demand of the gasifier is calculated at 81,480 odt.

Residues handling cost and capacity

Handling of residues, which is carried out by a front-end loader, is required when residues first arrive at the terminal storage or at the mill. Front-end loaders move the residues to temporary piles after being unloaded from trucks. Residues that are stored at storage require additional handling. In this paper, the handling of residues is referred to as pile management when it is carried out at the storage site. Handling of residues has a cost which is applicable to both types of residues. In the mathematical formulation, $\sigma_{j=1}$ and $\rho_{k=1}$ represent the handling cost at the terminal storage and the gasifier plant, respectively.

Handling cost includes operating and maintenance cost of a front-end loader. Operating cost consists of the fuel cost and the operator's wage. The capital cost of front-end loaders at the mill is excluded from calculations because the mill already owns as many of them as required. Therefore, handling capacity is assumed to be unlimited and the capital cost does not incur.

The bucket capacity of the front-end loader is assumed to be 3.5 m^3. Each cubic meter of residues, on average, corresponds to 0.39 odt. This is the average basic density of 13 wood species used in FPInterface (Charles Friesen, Senior Scientist at FPInnovations, personal communication, October 26, 2020). Thus, the mass of residues moved by the loader in one trip can be estimated as 1.365 odt. The loader is assumed to require an average of 5 min for each trip, which is a conservative assumption accounting for breakdowns and setup of the area. The throughput of the loader is calculated using Eq. (24).

$$\textit{Amount of residues handled in one hour by the front}-\textit{end loader} = \frac{\textit{Bucket capacity (odt)}}{\textit{Trip time (h)}} = \frac{1.365\ (odt)}{5\ (min)/60(\frac{min}{h})} = 16.38\ (\frac{odt}{h}) \tag{24}$$

At the pulp mill, each front-end loader consumes 30.1 L of diesel per hour. Assuming a diesel cost of \$1 per liter, a maintenance cost of \$36 per hour, and an operator's wage of \$55 per hour according to the pulp mill's recorded data, the total operating and maintenance cost of each front-end loader would be \$121.1 per hour. Dividing this cost by 16.38 (odt h^{-1}) results in a handling cost of \$7.39 per odt.

Preprocessing cost and capacity

The total annual cost of all preprocessing equipment is used to determine the unitary preprocessing cost of residues at the gasifier plant based on the annual feedstock demand. The total annual preprocessing cost is the sum of annual capital, insurance, and operating and maintenance costs. The annual capital cost of equipment is calculated using Eq. (25) [4].

Table 2
Details of the reclaiming equipment (Underground screw reclaimer).

Capital cost	502,546 CAD[a]
Delivery cost (10% of capital cost)	50,255 CAD[b]
Salvage value (10% of capital cost)	50,255 CAD[b]
Operating life	20 years[a]
Interest rate	6.5%[c]
Annual capital cost	48,876 CAD
Annual insurance cost (2.5% of annual cost)	12,564 CAD[c]
Annual operating and maintenance cost (10% of capital cost)	50,255 CAD[b]
Total annual cost	**111,695 CAD**

[a] [53].
[b] Assumption.
[c] [4].
[d] (Project Manager at the mill, personal communication, September 25, 2020).

Table 3
Details of the screening equipment (Acrowood Model 636 Disc Scalper).

Capital cost	94,025 CAD[a]
Delivery cost (10% of capital cost)	9,403 CAD[b]
Installation cost (2.6*Capital cost)	244,466 CAD[c]
Salvage value (10% of capital cost)	9,403 CAD[b]
Operating life	20 years[a]
Interest rate	6.5%[d]
Annualized capital cost	31,331 CAD
Annual insurance cost (2.5% of annual cost)	2,351 CAD[d]
Annual operating and maintenance cost (10% of capital cost)	9,403 CAD[b]
Total annual cost	**34,311 CAD**

[a] (Sales Head at Acrowood, personal communication, December 2, 2020).
[b] Assumption.
[c] (Project Manager at the mill, personal communication, September 25, 2020).
[d] [4].

Table 4
Details of the grinding equipment (Drop feed hog).

Capital cost	213,975 CAD[a]
Delivery cost (10% of capital cost)	21,398 CAD[a]
Installation cost (2.6*Capital cost)	556,335 CAD[b]
Salvage value (10% of capital cost)	21,398 CAD[b]
Operating life	20 years[a]
Interest rate	6.5%[c]
Annualized capital cost	71,301 CAD
Annual insurance cost (2.5% of annual cost)	5,349 CAD[b]
Annual operating and maintenance cost[d]	174,896 CAD
Total annual cost	**251,546 CAD**

a(Sales Manager at TerraSource, personal communication, December 1, 2020).
b(Project Manager at the mill, personal communication, September 25, 2020).
c[4].
d(Charles Friesen, Senior Scientist at FPInnovations, personal communication, November 3, 2020).

$$\textit{Annual capital cost of equipment} = \textit{Capital cost} * \frac{i(1+i)^n}{(1+i)^n - 1} - SV * \frac{i}{(1+i)^n - 1} \tag{25}$$

where i is the interest rate, n is operating life and SV is the salvage value of equipment. The data for capital cost and operating life of reclaimer are gathered from the Biomass Catalog (2007), which is based on the information provided by Antares Group Inc (Antares Group Inc., 2021). The capital cost is converted to present value using the inflation factor from the Bank of Canada [57]. The quotation and other details are shown in Table 2. Data on cost and operating life of scalping screen and drop feed hog are obtained from the vendors. Tables 3 and 4 show the cost details of the scalping screen and drop feed hog, respectively. It is assumed that the annual operating cost of the reclaimer and scalping screen is 10% of the capital cost. Operating and maintenance costs of the drop feed hog are calculated based on the venders' information.

Dry matter loss

During storage, a fraction of residues are lost due to microbial activity, commonly fungal attacks [10]. This fraction is referred to as dry matter loss and is shown by L in our formulation. According to [43], dry matter loss is 1% per month in ambient (open) piles. [10] approximated the monthly loss at 1.56% in dry basis in their literature review. For the sake of conservativity, we apply the same value to the monthly inventory of residues at the terminal storage and at the mill's storage.

Capacity and cost of storage at the gasifier plant (mill)

The storage capacity of the gasifier plant ($\pi^{max}_{k=1}$) at the mill is estimated at 12,870 odt. This capacity is associated with almost 5,500 m^2 of land requirement. The safety stock ($\pi^{min}_{k=1}$) is assumed to be 30 times the maximum average daily feedstock demand of the gasifier. The average daily demand of the gasifier is highest in April and is equal to 247 odt. Therefore, this makes the safety stock equal to 7,410 odt.

In an open pile storage system, the only incurred cost is the pile management cost. The pile management cost at the mill is similar to the residues' handling cost calculated in Section "*Residues handling cost and capacity*".

Capacity and cost of storage at terminal storage

The assumption is that the terminal storage capacity ($\varepsilon_{j=1}^{max}$) is identical to that of the mill storage. It is also assumed that no minimum inventory of residues is required to be maintained at the terminal storage. Thus, $\varepsilon_{j=1}^{min}$ is equal to zero in this case.

The storage cost at the terminal is comprised of (a) fixed land investment cost, (b) capital cost of a front-end loader, and (c) the pile management cost.

An online search was conducted to find commercial and industrial land listings in the pulp mill's region. The average land price of \$105 per m^2 was calculated based on the listings' prices and land area. Following this estimation, the land investment cost for terminal storage was approximated at \$577,500. Assuming an interest rate (i) of 6.5% and a service life of 20 years (n) for storage, the annualized investment cost of the open pile storage can be calculated using Eq. (26) [4].

$$Annualized\ investment\ cost = Land\ investment\ cost^{*}\frac{i(1+i)^n}{(1+i)^n-1} = \$\ 52,412 \quad (26)$$

Given a capital cost of \$650,000, a 10% delivery cost, a salvage value (SV) of 30% of the purchase price, and a service life (n) of 8 years, the annualized capital cost for the front-end loader can be calculated as \$98,078 using Eq. (25).

The pile management cost at terminal storage is equal to the residues' handling cost calculated in Section "*Residues handling cost and capacity*" (i.e., \$7.39 per odt).

Solution approach and model execution

The approaches for solving multi-objective optimization problems fall into three categories depending on the phase in which decision makers express their preferences for each objective. These include "a priori", "interactive", and "a posteriori" or generation methods. A priori method requires the decision makers to express their preferences before the solution process [23]). Goal programming is one of the widely used "a priori" methods for solving multi-objective optimization models [23]. It was recently applied to multi-objective biomass supply chain optimization problems for example in [25] and [29]. In goal programming, decision makers have to set weights and goals for each objective prior to solving the problem. Next, a preferred solution is found based on minimizing the weighted sum of deviations of objective functions from their goals. Setting goals and their importance may not be an easy task for the decision makers [19]. Another drawback of "a priori" method is that it only generates one solution, while decision makers might be interested in having a set of Pareto optimal solutions [31]. Pareto optimal solutions are solutions for which one objective cannot be improved without compromising at least one of the other objectives. In the "interactive" method, decision makers' inputs are given during the modeling process iteratively. This still requires the decision makers to define their preferences in order to obtain the results and this method is not able to provide the decision makers with the whole range of Pareto optimal solutions [19,31].

Contrary to the two mentioned methods, "a posteriori" method divides the solution process into two independent phases. First, the whole set of all preferred solutions are generated and then they are presented to the decision makers. Therefore, the decision maker's preferences are not needed in advance a set of Pareto optimal solutions are presented to them [31]. Two of the popular generation methods are weighted sum method and the ε-constraint method. Decision makers are able to see a representative subset of the Pareto front by implementing these methods. However, there are criticisms in performance of these two methods. The weighted method is only capable of generating efficient extreme solutions, and requires normalizing of the objective function values, which strongly influences the generated results. The ε-constraint method is free from these drawbacks. In this method, if the problem has N objectives, one objective is optimized, while the other (N-1) objectives are constrained by the epsilons [35]. However, this method has a weakness in computing the range of each objective. Also, there is no guarantee in the efficiency of the obtained solution when the ε-constraint is implemented [31]. A solution is guaranteed to be an efficient solution only if all the (N-1) objective functions' constraints become binding.

The augmented version of the ε-constraint method (AUGMECON) was developed by [31] to address the pitfalls associated with the ε-constraint method. AUGMECON is an "a posteriori" method that is similar to the conventional ε-constraint method in basics. It optimizes one objective, while the other objective(s) are constrained by the epsilon (s) [35]. AUGMECON addresses the problem of ε-constraint method in finding the range of each objective by using lexicographic optimization. It guarantees efficiency of all obtained solutions by ensuring that the slack and surplus variables of all (N-1) objective functions' constraints are zero; so that all (N-1) objective functions' constraints become binding. It also accelerates the computation process by exiting early from the iterations that lead to infeasible solution [31]. Readers are referred to [31]to find thorough explanation about the mathematical formulation and the Pareto set generation procedure of the AUGMECON method.

In the present study, it was not straightforward for pulp mill managers to express their preferences (i.e., goals and weights) for the total cost and maximum deviations from the safety stock objectives. Also, they were more interested in having a set of solutions rather than a single solution in order to see the possible trade-offs between the two objectives. For these reasons, the category of "a posteriori" methods that do not require decision makers' preferences during the solution process and can provide multiple solutions was selected. Among a posteriori methods, the AUGMECON method was ultimately chosen as the most appropriate solution approach because it does not suffer from the pitfalls of other "a posteriori" methods including the weighted and ε-constraint methods. AUGMECON has been frequently used for solving multi-objective biomass supply chain optimization problems in recent studies (e.g., [2,39,38,40,41,54]).

A set of 31 Pareto optimal solutions were generated by executing the bi-objective model on AIMMS 4.77 software [3]. The model was executed on a computer with Intel ® core ™ i7-6700 CPU @ 3.41 GHz processor and 16.0 GB RAM. The CPLEX 20.1 Solver was used to solve the model [24]. For the case study, each individual run of the resulted MILP model included 26,700 non-negative continuous decision variables, one integer decision variable and 13,469 constraints.

Results

Pareto optimal solutions

The Pareto optimal set generated by the AUGMECON method is shown in Fig. 2. The Pareto frontier displays the trade-off between the annual supply chain cost and the negative deviations from the safety stock. The shape of the curve shows the compromises between the two objectives.

In Solution I, the maximum negative deviation from the safety stock over a one-year planning horizon is zero, which means that the monthly inventory level never goes below the safety stock throughout the year. This is achieved in Solution I at the expense of having the highest total

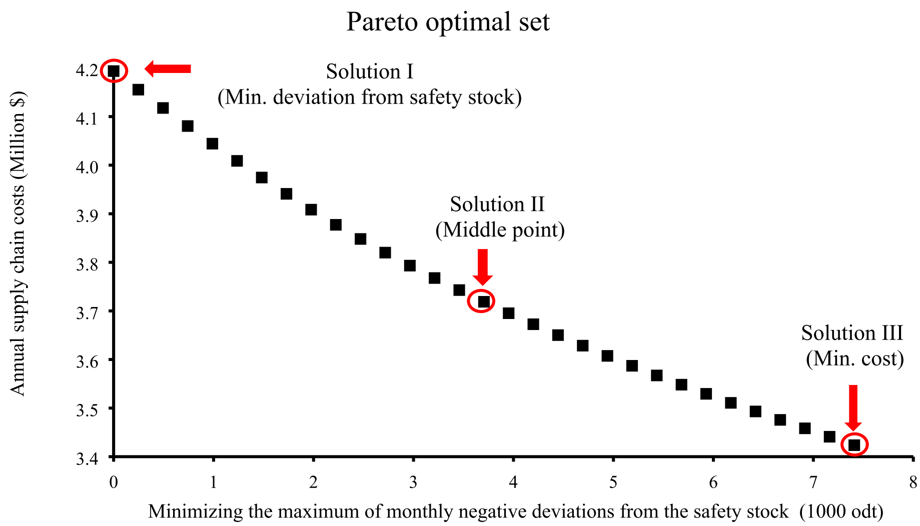

Fig. 2. Pareto frontier.

cost ($4.19 M) among all Pareto optimal solutions. On the other hand, Solution III has the lowest cost ($3.42 M). In this solution, no inventory of biomass is kept during the year, expect in months May, June, and July. As a result, the maximum negative deviation from the safety stock in Solution III has the highest value (7,409 odt) among the Pareto optimal solutions. The negative slope of the Pareto curve indicates that when moving from Solution I to Solution III, the cost decreases by approximately $770,000 (from $4.19 M to $3.42 M), while the maximum monthly negative deviation from the safety stock increases from zero to 7,409 odt.

Although the results for all Pareto optimal solutions are obtained, for brevity, only the results obtained for the two extreme points of the Pareto frontier (i.e., Solutions I and III) are presented and discussed in the following subsections. Solutions I and III represent the maximum possible trade-off between the objectives, as such comparing their results can provide more insight into the bi-objective model's outputs and performance across the Pareto optimal frontier as compared to any other points. The solution of the middle point in the Pareto curve (i.e., Solution II in Fig. 2) is used in Section "*Comparison of minimizing the maximum of deviations and minimizing the summation of deviations from the safety stock*" to compare the performance of the model under two different formulations. In the first formulation, the second objective function is modeled as the maximum of monthly inventory deviations from the safety stock, whereas under the other formulation, the second objective function is modeled as the summation of monthly deviations from the safety stock.

Flow of residues from supply sources to the gasifier plant

In all the Pareto optimal solutions including Solutions I and III, the binary variable for the establishment of the terminal storage becomes zero. Opening the terminal storage is not economical in any of the solutions because of the high establishment costs and additional costs associated with transporting biomass from the terminal storage to the plant. Therefore, there is no flow of residues from supply sources to the terminal storage, and all residues are sent directly to the gasifier plant.

Fig. 3 shows the annual cumulative flow of residues from each sawmill and collective cut blocks for Solutions I and III. The annual procured biomass for Solution I totals 90,183 odt, while this value is 81,491 odt for Solution III. The difference in annual biomass procurement in Solutions I and III is about 8,690 odt. This difference is attributed to the biomass amount that is necessary for satisfying the safety stock constraint and higher dry matter losses that occur due to maintaining higher inventory levels of biomass in Solution I. In both optimal solutions, the annual flow from Sawmills A, B, C, and D are identical and equal to the maximum biomass availability at the respective sawmills. This is because of the lower cost of delivered residues from these sawmills compared to Sawmill E. The annual cumulative flow of harvesting residues from cut blocks to the plant is 15,636 and 9,225 odt in Solutions I and III, respectively. The 6,411 odt of more harvesting residues flow to the plant in Solution I compared to Solution III occurs mainly in January to satisfy the safety stock requirement. In other months, the flow of harvesting residues is almost identical in both solutions and varies throughout the year to meet the gasifier's demand which cannot be met

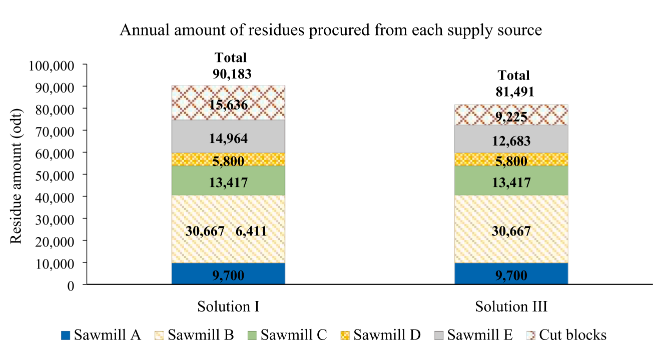

Fig. 3. Annual flow of residues from sawmills and cut blocks to the gasifier plant in Solutions I and III.

Table 5
Inventory of sawmill and harvesting residues maintained at the gasifier plant under Solutions I and III.

Month	Solution I (Sawmill residues), (Harvesting residues) (odt)	Solution III (Sawmill residues), (Harvesting residues) (odt)
January	(7,042), (368)	(0), (0)
February	(7,409), (0)	(0), (0)
March	(7,409), (0)	(0), (0)
April	(7,409), (0)	(0), (0)
May	(7,790), (0)	(23), (0)
June	(7,762), (0)	(115), (0)
July	(8,093), (0)	(566), (0)
August	(7,409), (0)	(0), (0)
September	(7,409), (0)	(0), (0)
October	(7,409), (0)	(0), (0)
November	(7,409), (0)	(0), (0)
December	(7,409), (0)	(0), (0)

by the lower-cost sawmill residues. The optimum flow from Sawmill E varies every month for both solutions and is higher for Solution I. Residues from Sawmill E are more expensive than those from other sawmills and many nearby cut blocks. Consequently, the mill has to purchase residues from this sawmill only to meet the portion of the demand that is not met by the low-cost sawmill and harvesting residues.

Inventory of residues at the gasifier plant

The monthly inventory of sawmill and harvesting residues that is maintained at the gasifier plant in Solutions I and III are tabulated in Table 5. As it can be seen from this table, in Solution I, the monthly inventory level always meets the safety stock and exceeds this amount in months of May, June, and July. As a result, in this solution, the monthly negative deviations from the safety stock are always zero. The monthly inventory level in Solution III, on the other hand, is always below the safety stock level. In fact, the inventory is zero in all months except in May, June, and July. Therefore, the maximum of monthly negative deviations from the safety stock in Solution III is the highest (i.e., 7,409 odt or safety stock level) compared to other Pareto optimal solutions. The inventory level in three months of May, June, and July increases under both solutions because of an increase in the gasifier's feedstock demand in August coupled with a reduction in the availability of cheap sawmill residues in June and July. Thus, the model prescribes keeping an inventory of lower-cost residues in the prior months to prevent the shortage and increased costs.

In both solutions, the inventory of residues is from sawmill residues, except in Solution I for the month of January, where 368 odt of harvesting residues is stored at the storage along with sawmill residues. This amount is replaced with sawmill residues in the next month. The reason that the model prescribes maintaining sawmill residues rather than harvesting residues is because sawmill residues require screening and further grinding. Thus, their utilization for the gasification is associated with additional cost compared to the stored harvesting residues. For this reason, from an economic point of view, it is preferred to store unground residues as safety stock and postpone the screening and comminution costs as much as possible.

Supply chain cost

The cost components of Solutions I and III are compared in Fig. 4. The total supply chain cost over a one-year planning horizon is $4,193,648 and $3,423,664 in Solutions I and III, respectively. Solution I has $769,984 higher cost in comparison with Solution III. This is caused by (1) the cost associated with procuring additional biomass to fully meet the safety stock constraint, and (2) increased monthly dry matter losses in Solution I. The major cost component in Solution I is the transportation cost of residues from supply points to the plant (38%), followed by the purchase cost of residues (28%). In Solution III, the contribution of purchase cost to the total cost is slightly higher (33%) than the transportation cost (32%). The reason that transportation has a higher cost than purchase in Solution I is mainly because 6,411 odt more harvesting residues are procured in Solution I in January to prevent negative deviations from the safety stock. This amount of harvesting residues is purchased at zero price but has a higher transportation cost. Thus, the increase in the procurement of this type of residues only adds to the cost of transportation without adding to the purchase cost. The next major cost component in both solutions is the handling cost of residues at the mill, which accounts for 16% and 18% of the total cost in Solutions I and III, respectively. Lastly, the costs associated with preprocessing of residues at the roadside and at the mill account for 7% and 10% of the total cost in Solution III, respectively. Contrary to Solution III, under Solution I, the preprocessing cost at the roadside is greater than the preprocessing cost at the mill (10% and 8%, respectively). The minor difference in percentages of preprocessing costs at the roadside and the mill between the solutions can be attributed to procuring more harvesting residues in Solution I compared to Solution III, which leads to an increase in the preprocessing cost at the roadside (i.e., grinding of harvesting residues to the trucks).

Table 6 compares the average per-unit total cost and costs of purchase, transportation, preprocessing, and handling of sawmill and harvesting residues in Solutions I and III. The average costs of purchase and transportation of sawmill residues are higher in Solution I compared to those in Solution III. This is due to the procurement of more sawmill residues from Sawmill E (which has the highest delivered cost among other sawmills) throughout the year in Solution I to meet the demand and prevent underachievement in the safety stock. Regarding the harvesting residues, their transportation cost is $28.18 per odt in Solution III and $44.49 per odt in Solution I. This major difference is because more residues should be procured from farther cut blocks in January to meet the safety stock requirement. Therefore, the average per-unit total cost of harvesting residues is higher and is $80.07 per odt in Solution I and $63.76 per odt in Solution III.

Comparison of minimizing the maximum of deviations and minimizing the summation of deviations from the safety stock

In Section "*Mathematical formulation*", the second objective function

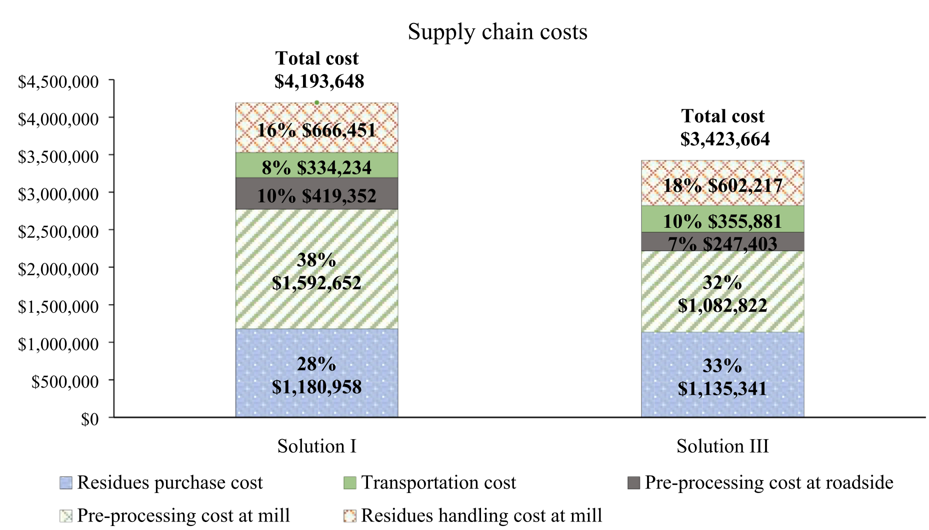

Fig. 4. Components of the optimum annual total cost in Solutions I and III.

Table 6
Average cost of sawmill and harvesting residues in Solutions I and III.

Solution	Type of residues	Average purchase price ($ odt^{-1})	Average transportation cost ($ odt^{-1})	Preprocessing cost at roadside ($ odt^{-1})	Preprocessing cost at the mill ($ odt^{-1})	Handling cost at the mill ($ odt^{-1})	Total cost ($ odt^{-1})
I (Min. Deviation)	Sawmill	15.75	12.03	NA	4.75	7.39	39.92
	Harvesting	0	44.49	26.82	1.37	7.39	80.07
III (Min. Cost)	Sawmill	15.64	11.39	NA	4.75	7.39	39.24
	Harvesting	0	28.18	26.82	1.37	7.39	63.76

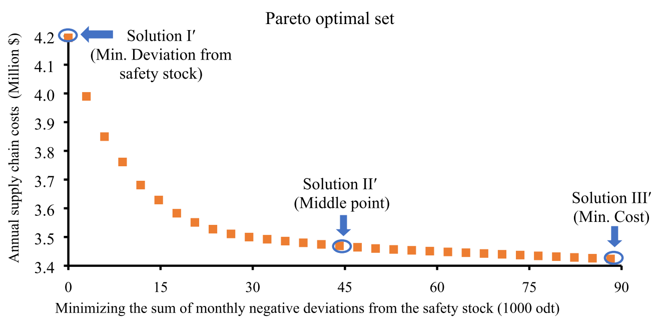

Fig. 5. Pareto frontier under minimization of sum of monthly deviations from the safety stock.

of the optimization model was formulated to minimize the maximum (over 12 months) of monthly negative deviations from the safety stock (hereinafter, referred to as Maximum deviation method). Another plausible approach to model the second objective function could be the minimization of the summation of monthly negative deviations from the safety stock (hereinafter referred to as Sum of deviations method). Following the latter approach, we could derive the trade-off between the summation of monthly deviations and the supply chain cost. In order to analyze the most important outputs of the optimization model using the Sum of deviations method and compare them with those of Maximum deviation method, we modified the second objective function of the optimization model from Eq. (2) to Eq. (27). In the next step, the new bi-objective optimization model was solved using the AUGMECON method for 31 iterations.

$$MinimizeZ_2 = \sum_{kt} s_{kt} \tag{27}$$

Fig. 5 shows the trade-offs between the total supply chain cost and the sum of deviations from the safety stock. Similar to the Maximum deviation method, in the Sum of deviations method, the supply chain cost decreases by gradual increase in the sum of deviations from the safety stock. Both methods generate similar solutions at extreme points of their Pareto frontiers which are depicted in Figs. 2 and 5. In Solutions I and I', there is no negative deviation from the safety stock throughout the planning horizon. Therefore, the sum and maximum of monthly negative deviations are zero with both methods resulting in the same total supply chain cost ($4.19 M) in Solutions I and I'. In Solutions III and III', on the other hand, the sum and maximum of monthly negative deviations are at their highest possible values. Therefore, in Solutions III and III', both approaches result in identical monthly negative deviations and equal supply chain cost of $3.42 M.

The total monthly negative deviations are equal for both methods in each iteration. For example, the middle points of the curves in Figs. 2 and 5, i.e., Solutions II and II', have equal total negative deviation of 44,105 odt from the safety stock during a year. However, in terms of cost minimization, the Sum of deviations method always performed better. For the solutions with the same total negative deviations, the Sum of deviations method always resulted in a lower cost compared to the Maximum deviation method. Solutions II and II', for instance have a total cost of $3.9 M and $3.5 M in the Maximum deviation and the Sum of deviations methods, respectively. The additional decrease in the cost at each iteration in the Sum of deviations method was achieved at the expense of having uneven monthly deviations from the safety stock. In simple words, the Sum of deviations method heavily lowers the inventory levels in the first and last months of the planning horizon, whereas the Maximum deviation method leads to an even monthly inventory level during a year. To illustrate this difference, monthly inventory levels in the middle points of the Pareto frontier of each method, Solutions II and II', are compared in Fig. 6.

As it is shown in Fig. 6, the optimal monthly inventory levels in the middle point solutions are lower than the safety stock in both the Sum of deviations and the Maximum deviation methods. However, in the Sum of deviations method, when sum of negative deviations from the safety stock is minimized, inventory levels from March to September are comparatively greater than the other months. Conversely, monthly inventory levels are relatively uniform and hovering between 5,000 and 6,000 odt when maximum of monthly negative deviations from the safety stock is minimized.

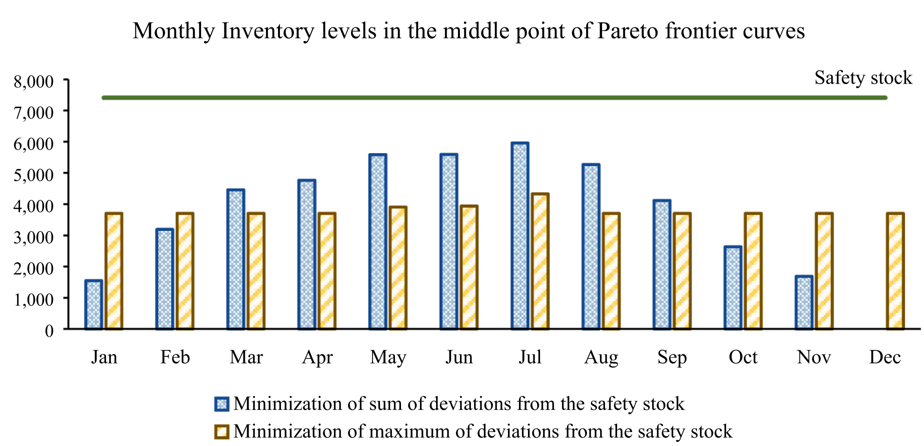

Fig. 6. Monthly inventory levels in the middle points of the Pareto frontier for Sum of deviations and Maximum deviation methods.

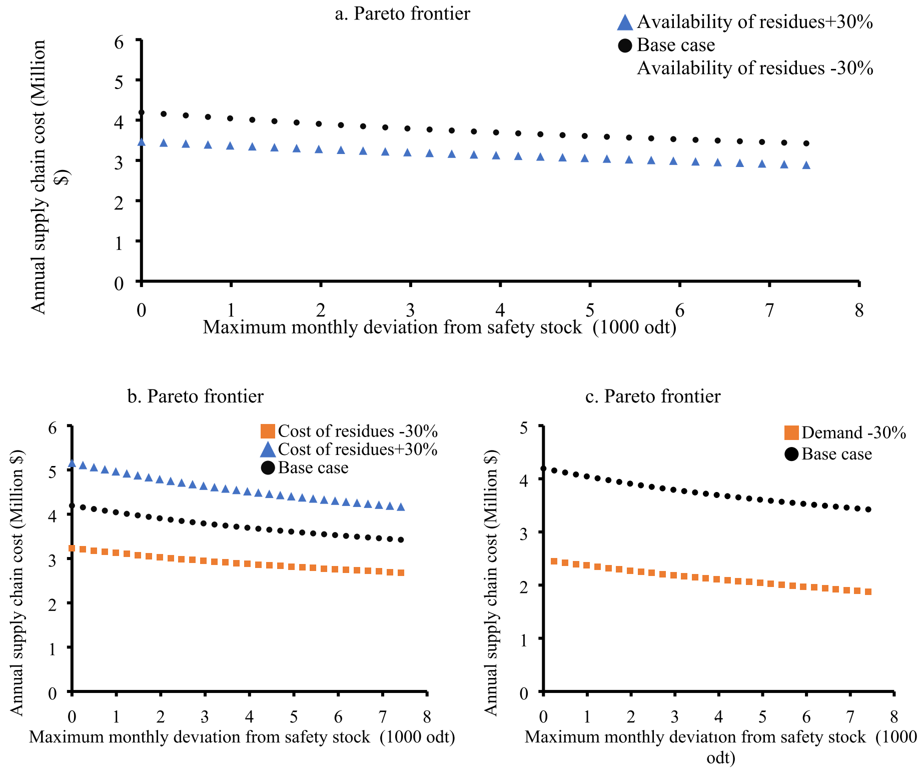

Fig. 7. Sensitivity analysis of the (a) availability of residues, (b) cost of residues, and (c) feedstock demand on the Pareto frontier.

Sensitivity analysis

The results of the bi-objective optimization model presented the trade-off between cost and inventory deviation objectives. By analyzing the trend in solutions of the Pareto frontier one could understand how the two objectives perform with respect to each other. It is also important to analyze the sensitivity of model results to the changes in supply chain parameters. Biomass availability, energy demand, and costs are among the main sources of uncertainty in biomass supply chains [11]. In this study, we performed sensitivity analyses to examine the impact of variations in biomass availability, cost, and feedstock demand on the Pareto frontiers. The mill managers suggested varying the availability, cost, and demand of residues by $\pm$ 30% and analyze the results. In all iterations, the feedstock demand increase of 30% resulted in infeasible solution due to limited preprocessing capacity at the mill. Graphs a, b, and c in Fig. 7 illustrate the trade-offs between objectives of cost and inventory deviation when $\pm$ 30% changes occur in availability, cost, and demand of residues. As illustrated in Graph 7-a, the 30% increase and decrease in the availability of both types of residues resulted in a decrease of 15%-18% and an increase of 23%-29% in the total supply chain costs of Pareto optimal solutions, respectively. In Graph 7-b, Pareto frontiers under 30% increase and decrease in the cost of residues have 22%–23% higher and lower costs, respectively, compared to the base case. A 30% decrease in the feedstock demand, on the other hand, resulted in a cost reduction between 40% and 45% among iterations with the same inventory objective value (Graph 7-c). The feedstock demand proved to be the most influential parameter on the supply chain costs, and therefore requires the most attention from the mill. Especially, the mill may have to consider preprocessing capacity upgrades in order to accommodate higher energy demands in the future.

Discussion

In previous studies including [6,44], authors developed single objective optimization models to minimize the upstream supply chains costs. The safety stock was fixed to a certain level and a single optimal cost was reported for the supply chain. In the present study, however, monthly inventory levels are allowed to go below the safety stock to derive the potential cost savings. Next, the total supply chain cost and the maximum of monthly negative deviations from the safety stock were formulated to be minimized as two separate objectives. Using the AUGMECON method, a set of Pareto optimal solutions was generated to display the trade-off between the two objectives. The trade-off indicates the cost savings resulted from the safety stock deviations. As shown in Fig. 2, the cost could decrease by 18% from \$4.19 M under Solution I to \$3.42 M under Solution III, while the maximum monthly negative inventory deviation increases from zero to 7,409 odt. From the generated Pareto optimal solutions in Fig. 2, the decision makers can choose a solution based on their risk tolerance towards the safety stock, planned budget, and other qualitative, non-technical, and experience-driven preferences.

The optimization model did not prescribe establishing the terminal storage in any of the Pareto optimal solutions since the storage capacity at the pulp mill is sufficient to hold the monthly biomass inventory. In addition, there are costs associated with opening of the terminal storage, handling of residues at the terminal, and transportation of biomass from the terminal to the plant which could be avoided to minimize the total supply chain cost. In other studies (e.g., [1,7,21]), however, opening of terminal storage(s) was essential to prevent biomass shortage due to limited storage capacity at the conversion facility.

The total procured biomass in Solution I was 11% (8,690 odt) higher than that in Solution III (Fig. 3). The higher amount of biomass procured in Solution I corresponds to 7,409 odt additional biomass serving the safety stock requirement and 1,290 odt of biomass that is lost during the storage over time. Consequently, the annual costs associated with biomass purchase, transportation, preprocessing, and handling were 18% (\$770,000) more in Solution I (Fig. 4). In all Pareto optimal solutions, the model prescribed procurement of all available residues at Sawmills A, B, C, and D. However, purchase of biomass from Sawmill E and harvesting cut blocks varied among solutions depending on the amount of negative deviations from the safety stock. This could provide managerial insight to the pulp mill related to supplier selection. Long-term supply contracts may be impacted by decisions regarding the inventory and flexibility in meeting the safety stock.

As shown in Fig. 4, biomass transportation accounts for over 32% of the total supply chain cost in Solutions I and III, whereas in other studies conducted in the Canadian context such as [6,9], the transportation cost was reported to account for 45%-80% of the total cost. The lower percentage of transportation cost in the present study compared to other works is because sawmills A and B, which supply 45%-50% of the gasifier feedstock demand, are located adjacent to the pulp mill site, and thus their transportation cost is zero. On the other hand, biomass purchase makes up over 28% of the total cost in Solutions I and III, whereas it accounted for minor portion of the total cost (1%–5%) in [6,9]. The reason behind having higher percentage of biomass purchase cost in the present study compared to previous works is that over 65% of the delivered biomass to pulp mill is supplied from sawmill residues that are not free of charge and are purchased at the cost of $20/odt. Contrarily, in [6,9], all sawmills residues were free of charge, resulting in low contribution of biomass purchase to the total supply chain cost. Other cost components including handling and preprocessing costs are falling in the range that was reported by [6,9].

In Section "*Comparison of minimizing the maximum of deviations and minimizing the summation of deviations from the safety stock*", by making comparison between the optimal solutions of the Sum of deviations and the Maximum deviation methods, it was realized that if the decision makers prioritize cost minimization, they could use the Sum of deviations method to derive the trade-off between total supply chain cost and deviations from the safety stock. However, in this method, they should accept the higher risks associated with high deviations from the safety stock that occur at the beginning and ending month of the year. The Maximum deviation method, on the other hand, generated Pareto optimal solutions in which monthly negative deviations from the safety stock were evenly distributed throughout the year, but at a higher supply chain cost. Thus, the Maximum deviation method approach decreases the probability of having zero to low biomass safety stock in some months and thus better serves the risk-averse decision makers.

Conclusions

In this study, a bi-objective optimization model is developed for the tactical planning of a forest-based biomass gasification supply chain. The model incorporated a safety stock constraint to hedge against the risk of biomass supply and demand mismatch. The objectives were to minimize the upstream supply chain costs and the negative inventory deviations from the safety stock. Minimizing the supply chain costs including purchase, transportation, storage, and preprocessing of biomass would improve the economic viability of the gasification project. Although the safety stock would minimize the consequences of unpredicted biomass shortage, it is associated with an additional cost of procurement, storage, and dry matter loss. This conflict was a major practical concern for managers at the mill. Allowing flexibility in the safety stock level to benefit from the possible cost savings in some months could address the concern over the conflicting objectives. Therefore, the bi-objective optimization model could provide the managers with a trade-off between the total supply chain cost and under-achievement in the safety stock. The model spanned a one-year planning horizon and prescribed the optimal monthly amount of residues to be (1) supplied from each supply source, (2) stored at conversion facility, (3) preprocessed, and (4) fed to the gasifier. Besides, it determined whether the establishment of a terminal storage would be required. The model was applied to a real case study of sawmill and harvesting residues' gasification at a Kraft pulp mill in British Columbia, Canada.

A set of Pareto optimal solutions was generated by solving the bi-objective model using the AUGMECON method and the AIMMS software. The analysis of the Pareto frontier showed a clear trade-off between the objectives of cost and maximum negative monthly deviation from the desired safety stock. Two extreme points of the Pareto frontier were analyzed and compared. The cost difference between a solution where there was zero negative deviation from the safety stock (Solution I) and a solution with minimum cost (Solution III) was estimated at $769,984. This difference was due to (1) the cost associated with procuring additional biomass to fully meet the safety stock, and (2) the higher dry matter losses that occur in Solution I. In both solutions, costs associated with biomass purchase and transportation were the major cost components, followed by biomass handling and preprocessing costs. The model did not prescribe establishing the terminal storage in any of the solutions as it was not economical. The feedstock demand of the gasifier was mainly met by procuring sawmill residues in both solutions due to their lower transportation and preprocessing costs compared to harvesting residues. However, in Solution I, to fully meet the safety stock, the model prescribed procuring 6,411 odt and 2,281 odt more of harvesting and sawmill residues in comparison with those in Solution III.

Sensitivity analysis was conducted on three parameters of residues supply amount, residues cost, and feedstock demand. The results of this analysis revealed the magnitude of the parameters' influence on the Pareto frontier and optimal cost. The feedstock demand proved to be the most impactful parameter of the supply chain.

The bi-objective model in this study was developed for the production of syngas from forest-based biomass at a specific Kraft pulp mill. However, with some modifications, the model can be applied to other cases of forest-based biomass gasification for production of other biofuels and bioenergy. The current model was deterministic and did not account for any unpredictable interruptions. Limited accessibility to forest cut blocks due to climatic conditions (i.e., summer wildfires and spring break-up) and temporary mill curtailments due to volatile market conditions would be among possible disruptions in biomass supply chains. Thus, one of the plausible future avenues for this study is to develop a stochastic bi-objective optimization model that incorporates uncertainty.

CRediT authorship contribution statement

Sahar Ahmadvand: Methodology, Software, Investigation, Validation, Data curation, Visualization, Writing - review & editing. **Maziyar Khadivi:** Methodology, Software, Investigation, Validation, Data curation, Visualization, Writing – original draft, Writing - review & editing. **Rohit Arora:** Methodology, Software, Investigation, Validation, Data curation, Visualization, Writing – original draft, Writing - review & editing. **Taraneh Sowlati:** Conceptualization, Methodology, Investigation, Validation, Resources, Supervision, Writing - review & editing, Project administration, Funding acquisition.

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.

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