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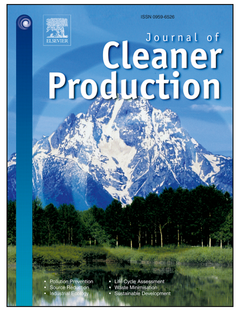

A hybrid multi-stage stochastic programming-robust optimization model for maximizing the supply chain of a forest-based biomass power plant considering uncertainties

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Abstract

Electricity generated from forest-based biomass is an attractive source of renewable energy. However, the cost of generating heat and/or electricity is relatively high due to the low energy density of wood, high moisture content and variations in its quality and availability. Models have been developed to optimize the supply chain and reduce the cost per kilowatt hour generated. This paper focuses on incorporating uncertainty in the supply chain of such a model. The model considers the tactical supply chain planning of a power plant over a one-year time horizon with monthly time steps. Uncertain parameters which impact the net profit of the power plant include 'biomass quality,' namely moisture content and higher heating value, and 'monthly available biomass' from different suppliers. Robust optimization is used to model uncertainty in the quality of biomass. Then a hybrid, multi-stage, 'stochastic programming-robust optimization' model is presented in order to simultaneously include uncertainty in biomass quality and biomass availability. It is demonstrated that the hybrid model takes advantage of both modelling approaches to balance the profit estimates and the tractability to various circumstances. The model provides solution considering all instances of the uncertain parameters within the defined sets and scenario tree. The results revealed a major trade-off between profit and range of biomass quality. Profit decreased by up to 23% when there was ±13% variation in moisture content and ±5% change in higher heating value. The model achieved a biomass purchase cost that was lower

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than the current commercial costs at the power plant. Implementing the model could prevent production curtailment and undesirable fluctuation in storage levels which occurred in the past due to variations in biomass availability and quality.

Keywords: Forest-based biomass, Bioenergy, Forest-based biomass supply uncertainty, Forest-based biomass quality uncertainty, Mixed integer programming model, Supply chain optimization, Multi-stage stochastic model, Robust optimization.

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1. Introduction

In the dynamic and competitive energy market, the transition to renewable energy sources presents a considerable challenge to traditional market-based solutions. Renewables are needed to reduce greenhouse gas emissions and the dependency on finite reserves of fossil fuel offer poorer short term prospects for industry and investors (Gomes et al., (2013), Handler et al., (2014) and San Miguel et al., (2015)). Forest-based biomass is a form of alternative energy sources which provides environmental and economic benefits in area rich in forested land and with advanced forest industries, such as in Canada (Bradley, 2010). Yet, the cost of generating heat and/or electricity from forest-based biomass falls short of competitive with conventional sources due to the properties of wood, such as a low energy density, high moisture content and uncertainty in its quality and availability (Liew et al., 2014).

To overcome short-comings in cost-effectiveness and to leverage forest biomass as a socially acceptable energy, strategies to achieve the desired cooperation between stakeholders, decision makers and all other players in the system must be identified. Barring technological breakthroughs, modeling based on game theory have been considered (for an introduction see Perc and Szolnoki (2010), Wang et al. (2015), Perc (2006, 2007)). The most expedient, short-term solution is to optimize the performance of the forest-based biomass supply chain to reduce costs. Shabani et al., (2013) provided a review of the literature on optimization models in forest bioenergy supply chains (Shabani et al., 2013).

Uncertainty in forest bioenergy supply chains exist partly due to economic fluctuations, which also affects other energy industries, yet additional complexities exist. Fundamentally, the characteristics of wood e.g., its non-homogeneous nature, affect the quality and fuel property of the biomass (Bowyer et al., 2012). Seasonal variations in quality and quantity of biomass occur because forest residue may not be accessible throughout the year and its quality (especially moisture content) changes in different seasons and during its storage. Moreover, ensuring a continuous supply of forest-based biomass typically requires multiple sources which introduces variation in biomass quality (Gold and Seuring, 2011). Beyond the quality of biomass, other sources of uncertainty exist, such as the interdependency between different forest products sectors. When the raw material of one sector, such as wastes from lumber production, is used by another, such as the bioenergy sector, unforeseeable circumstances in one sector can affect the

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other sector and its supply chain. Therefore, managing uncertainty is paramount when designing supply chain optimization models. If uncertainty is ignored, the solution of the optimization model may be either infeasible, suboptimal or both (Bertsimas et al., 2007) and may not provide a reliable solution (Wu et al., 2013).

In selecting the most suitable approach for modelling with uncertainty, one must consider i) the characteristics of the data, ii) the source of available data, iii) the computational effort and time needed to solve the model, and iv) the degree of sophistication that can be handled and accepted by the users and decision makers. These approaches range from scenario analysis to more advanced techniques such as stochastic programming and robust optimization (Birge and Louveaux, 1997, Bertsimas and Sim, 2003).

Stochastic programming is adequate and effective when the probability distribution of uncertain parameters is known and it is possible to define potential scenarios. However, the stochastic programming model is computationally intractable when the value of an uncertain parameter covers a continuous range. One can manage this by creating a set of scenarios derived from discretizing the uncertainty sets, however, the total number of scenarios grows exponentially when dealing with a sequence of scenarios, e.g. a scenario tree resulting in computationally intractable models (Ben-Tal et al., 2000). A review of stochastic programming optimization in the forest industry and biomass and biofuels supply chains is provided in our previous publication (Shabani et al. 2014). Another alternative, however, is to use the robust optimization method which is attractive because it can be solved effectively and efficiently using the current powerful solvers if a tractable uncertainty set is selected (Ben-Tal et al., 2000). Moreover, contrary to stochastic programming, in order to incorporate uncertainty in robust optimization only a range of uncertain parameter (instead of its probability distribution) is required (Gabrel et al., 2013).

Robust optimization has been used and applied in several fields of study, such as facility location and inventory management (Gülpınar et al., 2013, Solyali et al., 2012), resource allocation and project management (Wiesemann et al., 2012), and also in specific supply chain optimization problems such as the models in the refinery industry (Leiras et al., 2010). Palma and Nelson (2009) applied the robust optimization approach to the forest industry to incorporate uncertainty in products volume and demand to support the decision of harvest scheduling. In a second study, they used robust optimization in a bi-objective planning model with random objective weights for forest planning (Palma and Nelson, 2010). Other researchers have employed robust models in forestry applications such as Alvarez and Vera (2011) & Kazemi Zanjani et al. (2010a) for optimizing sawmill planning; Tay et al. (2013) for integrating black liquor biorefineries for energy production; Bredström et al. (2013) for planning a biofuel heating plant; and Carlsson et al. (2014) for considering customer demand in the pulp and paper industry. The method used by Kazemi Zanjani et al. (2010a), which combined robust optimization and stochastic programming, was of interest to us and served as a model for developing our hybrid 'stochastic programming-robust optimization' model. Their method was based on the earlier definition of robust optimization (Mulvey et al. (1995)'s definition) which included minimization of variations in the model solution. The current definition of robust optimization is based on optimizing the worst case instead which was not used in their study.

While a few studies have considered uncertainty in bioenergy supply chains in general (Kim et al. 2011; Chen and Fan 2012), to the best of our knowledge, our approach in modeling uncertainty in biomass quality and availability in forest-based biomass to bioenergy supply chains is novel. Based on the results of the sensitivity analysis in Shabani and Sowlati (2013), biomass availability and quality were among the most influencing uncertain parameters. Previously a two-stage stochastic optimization model is developed to consider uncertainty in the forest-based biomass availability (Shabani et al. 2014). Our previous work is extended here and a hybrid model to account for uncertainties in both biomass quality and biomass availability is developed. Our model is constructed by first modeling moisture content (MC) and higher heating value (HHV) using a robust optimization formulation, then, by introducing the uncertainty in monthly available biomass with a multi-stage stochastic programming model. It is demonstrated how our hybrid multi-stage stochastic programming-robust optimization model has an appropriate balance between solvability of the model and conservatism of the optimal solution.

The rest of this paper is structured as follows. In Section 2, the problem of optimizing a forest biomass power plant supply chain is described. In Sections 3 and 4, the structure and formulation of the developed optimization models are presented. The results are provided in Section 5 and the main conclusions of the study are included in Section 6.

2. Problem description

A brief overview of the supply chain considered in this study is provided here, but a more detailed explanation can be found in Shabani and Sowlati (2013). Our model is based on a forest biomass power plant in Canada. Its supply chain consists of several different suppliers that provide different types of forest-based biomass to the plant, an open storage yard for storing the mix of biomass, and a power plant that generates electricity. The power plant has fixed contracts with some suppliers and consequently has to buy the residues they produce with a fixed cost. However, these suppliers have no obligation to produce biomass for the power plant when they do not produce their main products. The rest of the suppliers have no long-term contract with the power plant. The power plant has to generate enough electricity (called the firm load) to meet its customer's need throughout the year. It also has the option to generate more electricity than the firm load (called surplus load) to sell it based on the open market price whenever it is profitable. The decision about whether or not to produce the surplus load is made in the beginning of each year and will not change during the year.

Different types of biomass including bark, sawdust, shavings and roadside logging debris are received from different suppliers. These are then mixed and kept in a storage yard until combusted. There are two upper limits for storing biomass above which additional costs related to hiring an extra person and an extra piece of equipment for material handling would be imposed. There is a lower limit at which point the quality of biomass deteriorates because the pile does not generate sufficient internal heat (Fuller, 1985). The electricity generation at the power plant is based on a conventional power cycle and includes a boiler, a turbine, a condenser, a high voltage step up transformer, a solid fuel handling system, an ash removal/handling system, other steam cycle auxiliary pieces of equipment, multiple cyclones, and an electrostatic precipitator.

In Shabani and Sowlati (2013), a mixed integer non-linear model was developed to optimize the supply chain over a one-year planning horizon with monthly time steps. The decision variables of the model were the amount of biomass to purchase, store and consume from each supplier in each month, and whether or not to generate the surplus load. The objective function was to maximize the profit which is the revenue from selling the firm and surplus loads to the customers minus purchase, transportation, production, storage and ash removal costs.

A number of parameters of the deterministic model presented in Shabani and Sowlati (2013) may have variations. As previously mentioned, the quality of biomass is highly variable. Wood is a heterogeneous material and its quality varies in different parts of the tree, different species and different periods (Demirbaş, 2001 and 2003, Carlsson et al., 2009) and also differ in different types of biomass (e.g. bark, sawdust, shavings) (Lehtikangas, 2001). Biomass quality plays an important role in the total amount of electricity generated and the cost per kilowatt hour (Saidur et al., 2011). The other major source of uncertainty stems from the supply of by-products. The suppliers to the power plant are several sawmills and a plywood mill and their production capacity is tightly dependent on housing and lumber markets, making the availability of biomass uncertain. If uncertainty in these parameters is ignored, the solution may vary significantly given any perturbation in them and may become non-optimal or even infeasible. The original mixed integer non-linear model (Shabani and Sowlati 2013) was then reformulated in Shabani et al. (2014) into a linear model in order to be able to include uncertainty in biomass availability in a two-stage stochastic optimization model. However, the uncertainty in the quality of biomass was not considered.

According to the power plant managers, it seemed appropriate to assume that biomass amount was known for the first three months of the year and then it could stay the same (average scenario), increase or decrease by 20% (high or low scenarios) for each of the following three-month intervals over the year. Moreover, since all the suppliers were located in the same area and cover the same market, it was assumed that the change in the amount of biomass supply would be the same for all suppliers, for instance, if the market was promising, then all the suppliers would have 20% increase in their production for three months. Consequently, the total number of scenarios over a year was calculated by having three supply scenarios (high, average and low) for each three-month interval from month 3 to month 12, knowing the biomass supply for the first three months with certainty, which equals to 3^3=27. These 27 scenarios were considered in a multi-stage stochastic optimization model. The probability of occurrence was assumed to be 1/27 for each scenario.

The probability distributions of MC and HHV were not known and only their possible variation ranges were available. Different scenarios could be obtained for MC and HHV by discretizing their ranges. However, if these scenarios were combined for different biomass types, suppliers and months, the total number of scenarios would be very large even with a small number of discretized scenarios. Therefore, due to unavailability of probability distribution of biomass quality as well as dimensionality issue, robust optimization is used in the current study to include the uncertainty in biomass quality into the decision making process. Furthermore, to include uncertainty in both biomass quality and availability, a hybrid multi-stage stochastic programming-robust optimization model is suggested in Section 4. The stochastic programming of the hybrid model has a different structure than the model in Shabani et al. (2014) and instead of a two-stage stochastic programming model, a multi-stage stochastic optimization model is used for including uncertainty in biomass availability in order to have the variations in biomass availability according to scenarios in the decision tree.

3. Robust optimization model

The uncertainty in biomass quality was incorporated, using robust optimization, into the previously designed linear optimization model presented in Shabani et al. (2014) model. MC and HHV were not correlated because HHV was calculated based on dry biomass. MC and HHV together produce another parameter called energy value. Based on the data provided by the power plant, the range of variation in MC was 25-35% with an average of 30%, and it was 8000-9000 BTU/lb (4.69-5.27 MWh/ton) for HHV with an average of 8500 BTU/lb (4.98 MWh/ton).

The formulation of robust optimization depends on the definition of a robust solution. A robust solution is one that must be feasible for any realization of the uncertain parameter. This approach was originally proposed by Soyster (1973) and is known to be an “ultraconservative strategy”. Ben-Tal et al. (2000) recommended less conservative approaches by using different set of uncertainties such as ellipsoidal uncertainties. Depending on the type of the uncertainty set, the robust optimization model could become nonlinear.

Bertsimas and Sim (2003, 2004) suggested an approach that uses the idea of “budget of uncertainty” to control the level of conservativeness. In this method, only some of the uncertain parameters deviate from their nominal values simultaneously. Using this definition, a constraint is immunized against uncertainty by determining the size of the buffer or a "protection function" of it. This protection function is an optimization model itself and its dual is embedded in the original model. Given the linearity of the original problem, the robust counterpart is also a linear problem with a modified feasible region. In all of these methods, the solution is optimized based on the worst case, which is the most unfavourable realization of the uncertainty. The worst case can be selected differently, too, either from a finite number of scenarios, such as historical data, or continuous, convex uncertainty sets, such as polyhedrons or ellipsoids. For a recent review of robust optimization the reader is referred to Gabrel et al. (2013).

The classic robust optimization formulation derived from Ben-Tal et al. (2009) with a box uncertainty set which is available in the AIMMS software package is used. It helped to have a tractable model providing a feasible solution for all MC and HHV ranges. This model will inevitably provide lower profit estimates than the deterministic model because it optimizes the worst case.

The notations of model sets, parameters and variables of robust optimization model are shown in Table 1.

Table 1: Parameters, sets, decision variables of the robust optimization model

Parameters	
$AshC$	Average ash content of biomass mixture (%)
$AshHC$	Unit cost of handling ash ($/green ton)
$BC_{s,p}$	Unit cost of biomass type p purchased from supplier s ($/green ton)
$efficiency$	System efficiency (30%)
$EV_{s,p,t}$	Energy Values of biomass type p from supplier s in month t (MWh/green ton)
FD	'Firm Demand' required to be met each year (MWh)
FP	Unit price for the firm demand ($/MWh).
$HHV_{s,p,t}$	Higher Heating Value of biomass type p from supplier s in month t (MWh/dry ton)
$MaxF_{s,t}$	Maximum available biomass from supplier s in month t (green ton)

$MaxS$	Absolute maximum storage levels (green ton)
$MC_{s,p,t}$	Moisture Content of biomass type p purchased from supplier s in month t (%)
MFD_t	Monthly 'Firm Demand' in month t if surplus load is not produced (MWh)
PC	Production Cost including water, sewer and chemical costs ($/MWh)
PSC	Penalty cost if storage level is above SDL or SUL ($)
QRF	Percent reduction in biomass quality if storage level is below SLL (%)
$Ratio_{s,p,t}$	Ratio of biomass type p produced in supplier s in month t (%)
SD	Surplus Demand that the company can optionally produce over a year (MWh)
SDL	Storage Desired Level, the level at which a penalty cost occurs for additional equipment and additional staff (green ton)
SLL	Storage Lower Limit, the level at which biomass quality decreases due to insufficient time to produce internal heat (green ton)
SP	Unit price for Surplus Demand ($/MWh)
SUL	Storage Upper Limit, the level at which a penalty cost is added due to the use of additional equipment and staff as well as high fire risk (green ton) ($SUL \geq SDL$)
$TargetS$	Target Storage level (green ton)
$TC_{s,t}$	Unit transportation cost from supplier s in month t ($/green ton)
WH_t	The amount of power plant's working hours in month t (hr)
$\widetilde{\mathrm{MC}}_{\mathrm{s,p,t}}$	Every value of moisture content of biomass type p purchased from supplier s in month t (%) that belongs to an uncertainty range
$\widehat{\mathrm{MC}}_{\mathrm{s,p,t}}$	The positive constant perturbation in $\mathrm{MC}_{\mathrm{s,p,t}}$
ψ	The adjustable parameter controlling the size of uncertainty set
Sets	
$Product$	Types of biomass (p ∈ {Bark, Sawdust, Shavings, Roadside Logging Debris (RLD)})
$Suppliers$	List of suppliers (s∈{S_1, …, S_8})

$Time$	Time period (t ∈ {Jan, Feb, ..., Dec})
Decision Variables	
$C_{s,t}$	Amount of biomass from supplier s consumed in month t (green ton)
E_t	Amount of electricity generated in month t (MWh)
$F_{s,t}$	Amount of biomass purchased from supplier s in month t (green ton)
$S_{s,t}$	Amount of biomass from supplier s stored in month t (green ton)
SB	1 if surplus electricity is produced in a year, 0 otherwise (binary)
$U_{s,t}$	A new set of auxiliary decision variables related to $C_{s,t}$ for the robust optimization model
X_t	1 if storage is higher than SDL in month t, 0 otherwise (binary)
Y_t	1 if storage is higher than SUL in month t, 0 otherwise (binary)
Z_t	1 if storage is lower than SLL in month t, 0 otherwise (binary)
τ	The objective function of the robust optimization model

The objective function of the robust optimization model is

$$\text{Min } \tau \quad (1)$$

Where τ is connected to the deterministic objective function as shown in Equation 2:

$$Profit \leq \tau \quad (2)$$

The objective function of the deterministic model ($Profit$) was to maximize the profit, including revenues from selling the firm and surplus electricity loads to the customer, if the surplus load is produced, minus biomass procurement (purchase and transportation) cost, ash removal cost, storage penalty cost and production cost.

$$Profit = FP \times FD + SP \times SD \times SB - \sum_{s,t}\left(\sum_p BC_{s,p} \times Ratio_{s,p,t} + TC_{s,t}\right) \times F_{s,t} - \sum_t AshHC \times AshC \times \sum_s C_{s,t} - \sum_t PSC \times (X_t + Y_t) - (WC + ChC + SC) \times \sum_t E_t \quad (3)$$

Other constraints of the model are as follows:

For suppliers with a fixed contract, the amount of biomass purchased from supplier (s) in month (t) has to be equal to the maximum available biomass from supplier (s) in month (t):

$$F_{s,t} = MaxF_{s,t} \qquad [s \in \{S_1, \ldots, S_4\}, t \in \{Jan, \ldots, Dec\}] \qquad (4)$$

For suppliers without a fixed contract, the amount of biomass purchased from supplier (s) in month (t) has to be less than or equal to the maximum available biomass from supplier (s) in month (t):

$$F_{s,t} \leq MaxF_{s,t} \qquad [s \in \{S_5, \ldots, S_8\}, t \in \{Jan, \ldots, Dec\}] \qquad (5)$$

The total storage level of biomass from all suppliers (s) stored in month (t) has to be less than or equal to the maximum storage level:

$$\sum_s S_{s,t} \leq MaxS \qquad [t \in \{Jan, \ldots, Dec\}] \qquad (6)$$

The total storage level of biomass from all suppliers in the last month has to be equal to a target storage level which is set by the power plant managers.

$$\sum_s S_{s,Dec} = TargetS \qquad (7)$$

The storage level of biomass received from supplier (s) and stored in month (t) is equal to the storage level of biomass received from supplier (s) and stored in previous month ($t-1$) plus the biomass purchase from supplier (s) in month (t) minus biomass consumption from supplier (s) and stored in month (t). For the first time step, the initial storage level for each supplier has to be known:

$$S_{s,t} = S_{s,t-1} + F_{s,t} - C_{s,t} \qquad [s \in \{S_1, \ldots, S_8\}, t \in \{Jan, \ldots, Dec\}] \qquad (8)$$

As mentioned earlier, the electricity production in month (t) has two parts: the firm load and the surplus load. If the surplus load is produced, E_t equals the total firm and surplus load over a year multiplied by the ratio of working hours in month (t) divided by the total working hours in a year ($WH_t / \sum_t WH_t$). If only the firm load is produced, the electricity demand in month (t) equals to the monthly firm load:

$$E_t = (FD + SD) \times \frac{WH_t}{\sum_t WH_t} \times SB + MFD_t \times (1 - SB) \qquad [t \in \{\text{Jan, …, Dec}\}] \quad (9)$$

On the biomass side, the amount of electricity generated in month (t), E_t, equals the total biomass consumption in month (t) multiplied by the total ratio of biomass type (p) for supplier (s) in month (t), the energy value of biomass type (p) from supplier (s), system efficiency, and the ratio of quality reduction factor if the storage level in month (t) is lower than the storage lower level (SLL). If the forest biomass pile is not high enough, its quality will reduce (a factor (QRF) is considered in the equation) because enough internal heat could not be generated (Fuller, 1985):

$$E_t = \sum_s C_{s,t} \times \sum_p (Ratio_{s,p,t} \times EV_{s,p,t}) \times efficiency \times (1 - QRF \times Z_t)$$

$$[t \in \{\text{Jan, …, Dec}\}] \quad (10)$$

In Equation 10, Energy value ($EV_{s,p,t}$), is calculated based on the higher heating value and the moisture content of biomass type p purchased from supplier s in month t ($HHV_{s,p,t}$, $MC_{s,p,t}$) (Bowyer et al., 2007):

$EV_{s,p,t} = HHV_{s,p,t} \times (1 - MC_{s,p,t})$ [for $s \in \{S_1, …, S_8\}$, $t \in \{\text{Jan, …, Dec}\}$ and $p \in \{$Bark, Sawdust, Shavings, Roadside Logging Debris (RLD)] (11)

If only uncertainty in moisture content is included in the model, Equation 10 has to be replaced by the following Equation:

$$E_t \leq \sum_s C_{s,t} \times \sum_p (Ratio_{s,p,t} \times \mathrm{HHV_{s,p,t}} \times (1 - \widetilde{\mathrm{MC}}_{\mathrm{s,p,t}})) \times efficiency \times (1 - QRF \times Z_t)$$

$$[\forall\ \widetilde{\mathrm{MC}}_{\mathrm{s,p,t}} \in [25,30],\ t \in \{\text{Jan, …, Dec}\}] \quad (12)$$

The robust counterpart of Equation 12 is as follows (see Li and Floudas, 2012):

$$E_t \leq \sum_s C_{s,t} \times \sum_p (Ratio_{s,p,t} \times \mathrm{HHV_{s,p,t}} \times (1 - \widehat{\mathrm{MC}}_{\mathrm{s,p,t}})) \times efficiency \times (1 - QRF \times Z_t) + \psi \sum_s U_{s,t} \times \sum_p (Ratio_{s,p,t} \times \mathrm{HHV_{s,p,t}} \times (1 - \widehat{\mathrm{MC}}_{\mathrm{s,p,t}})) \times efficiency \times (1 - QRF \times Z_t) \quad (13)$$

$$-U_{s,t} \leq C_{s,t} \leq U_{s,t}, U_{s,t} \geq 0 \quad (14)$$

Where $U_{s,t}$ is a new set of decision variables, $\widehat{\mathrm{MC}}_{\mathrm{s,p,t}}$ is the positive constant perturbation in $\mathrm{MC}_{\mathrm{s,p,t}}$ and ψ is the adjustable parameter controlling the size of uncertainty set. Notice that Constraint 10 is converted to inequality in order to make sure it can be met for all realization of $\mathrm{MC}_{\mathrm{s,p,t}}$. The same formulation can be written for uncertainty in $\mathrm{HHV}_{\mathrm{s,p,t}}$. When uncertainty in both parameters is included, the term $\mathrm{HHV}_{\mathrm{s,p,t}} \times (1 - \mathrm{MC}_{\mathrm{s,p,t}})$ is replaced by $\mathrm{EV}_{\mathrm{s,p,t}}$ and the formulation is written for this parameter with the range derived from $\mathrm{HHV}_{\mathrm{s,p,t}}$ and $\mathrm{MC}_{\mathrm{s,p,t}}$ ranges.

All continuous variables have to be non-negative:

$$F_{s,t}, S_{s,t}, C_{s,t}, E_t \geq 0 \qquad [s \in \{S_1, \ldots, S_8\}, t \in \{\text{Jan}, \ldots, \text{Dec}\}] \quad (15)$$

Additional constraints have to be added for the definition of binary variables X_t, Y_t and Z_t. Moreover, Equation 8 contains the multiplication of a binary variable Z_t and a continuous variable $C_{s,t}$ which is non-linear and can be converted to a linear constraint. It can be done by replacing $Z_t \times \sum_s C_{s,t}$ with an additional continuous variable ($L_t \geq 0$) and additional constraints (16, 17 and 18). M is a sufficiently large number.

$$L_t \leq M \times Z_t \qquad [t \in \{\text{Jan}, \ldots, \text{Dec}\}] \quad (16)$$

$$L_t \leq \sum_s C_{s,t} \qquad [t \in \{\text{Jan}, \ldots, \text{Dec}\}] \quad (17)$$

$$L_t \geq \sum_s C_{s,t} - M \times (1 - Z_t) \qquad [t \in \{\text{Jan}, \ldots, \text{Dec}\}] \quad (18)$$

The model is now a mixed integer linear programming (MILP) model which is solved using the AIMMS software and CPLEX solver.

4. Hybrid multi-stage stochastic programming-robust optimization model

The scenario tree for the multi-stage stochastic programming model is shown in Figure 1. The number shown on each arch represents the rate of change from the average scenario in the available biomass from supplier *s* in each stage. The scenario tree contains four stages and each stage includes three months (Stage 1: Jan, Feb, and Mar; Stage 2: Apr, May, and Jun; Stage 3:

Jul, Aug, and Sep; and Stage 4: Oct, Nov, and Dec). As mentioned earlier, it is assumed that variations in biomass availability are stationary during the three months in each stage. The robust optimization model is similar to the model explained in Section. 3. The formulation of the hybrid model is presented here.

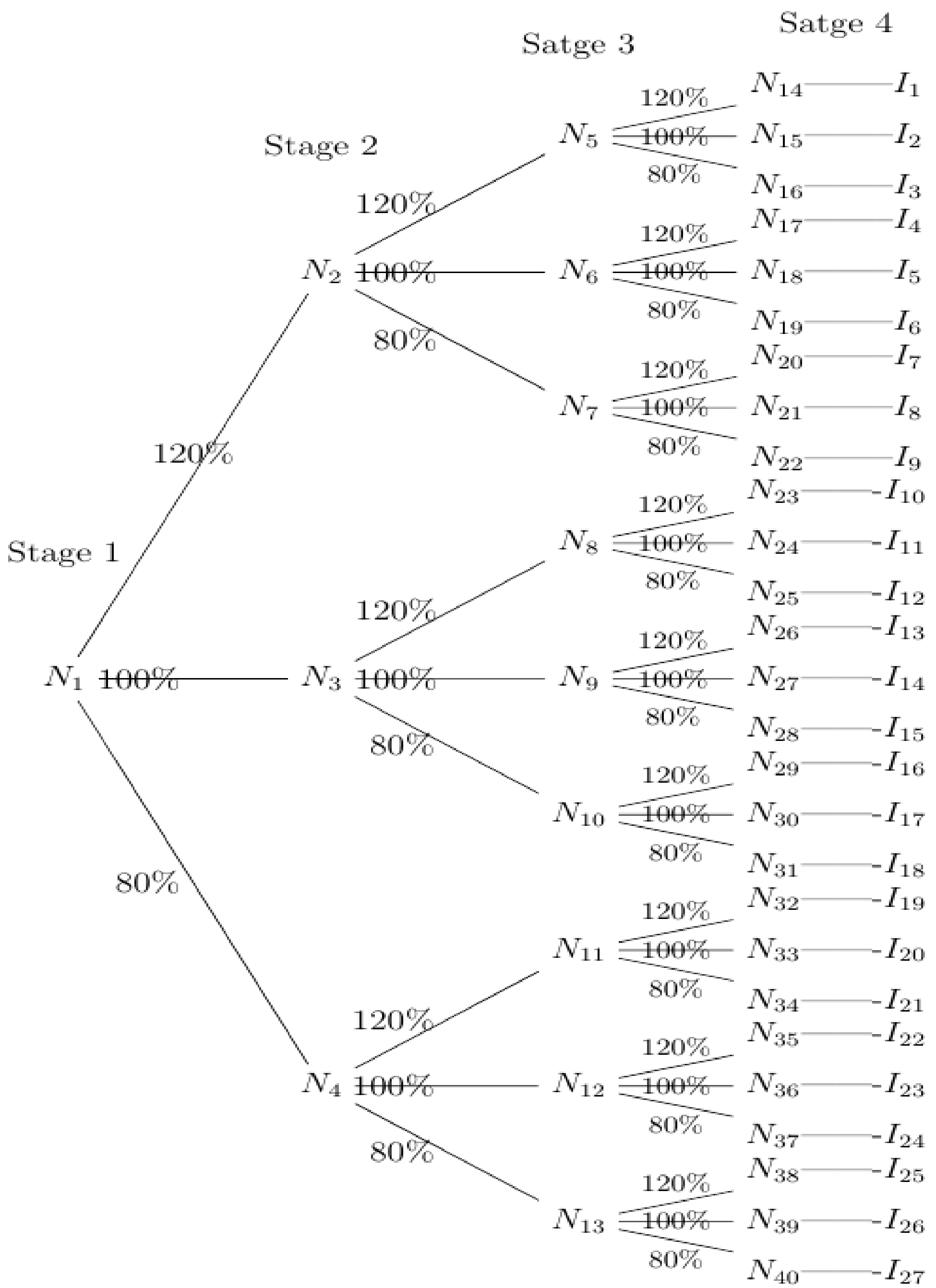

Figure 1: The scenario tree for uncertainty in biomass availability

For the hybrid model, the decision variables are indexed over each scenario, too. The notations of parameters, sets and decision variables of the multi-stage stochastic model are provided in Table 2.

Table 2: Stochastic model decision variables

Parameters	
$MaxF_{s,t,i}$	Maximum available biomass from supplier s in month t for scenario i (change by ±20% in each node of the tree as shown in Figure 1)
Pr_i	Probability of occurrence of scenario i (1/27) ($\sum_i Pr_i = 1$).
Sets	
Nodes	Set of nodes of the Tree (n∈{N_1, …, N_{40}}).
Scenarios	List of scenarios (i∈{I_1, …, I_{27}}).
Decision Variables	
$F_{s,t,i}$	Amount of biomass purchased from supplier s in month t for scenario i (green ton).
$S_{s,t,i}$	Amount of biomass stored from supplier s in month t for scenario i (green ton).
$C_{s,t,i}$	Amount of biomass consumed from supplier s in month t for scenario i (green ton).
$E_{t,i}$	Amount of electricity generated in month t for scenario i (MWh).
SB_i	1 if surplus electricity is produced in a year, 0 otherwise for scenario i (Binary)
$X_{t,i}$	Binary variable, 1 if $S_{s,t,i}$ is higher than the desired storage level (SDL) in month t for scenario i.
$Y_{t,i}$	Binary variable, 1 if $S_{s,t,i}$ is higher than the upper storage limit (SUL) in month t for scenario i.
$Z_{t,i}$	First stage binary variable, 1 if $S_{s,t,i}$ is less than lower storage limit (SLL) in month t for scenario i.

The objective function is to maximize the expected profit of all scenarios:

$$Min\ \tau \tag{19}$$

$$\left(\sum_i Pr_i \times\ Profit_i\right) \leq \tau \tag{20}$$

Where $Profit_i$ equals revenues minus costs as shown in Equation 21:

$$Profit_i = FP \times FD + SP \times SD \times SB_i - \sum_{s,t}\left(\sum_p BC_{s,p} \times Ratio_{s,p,t} + TC_{s,t}\right) \times F_{s,t,i} - \sum_t AshHC \times AshC \times \sum_s C_{s,t,i} - \sum_t PSC \times \left(X_{t,i} + Y_{t,i}\right) - (WC + ChC + SC) \times \sum_t E_{t,i} \tag{21}$$

Subject to:

$$F_{s,t,i} = MaxF_{s,t,i} \qquad [s \in \{S_1,\ldots,S_4\},\ t \in \{Jan,\ldots,Dec\},\ i \in \{I_1, \ldots, I_{27}\}] \tag{22}$$

$$F_{s,t,i} \leq MaxF_{s,t,i} \qquad [s \in \{S_5,\ldots,S_8\},\ t \in \{Jan,\ldots,Dec\},\ i \in \{I_1, \ldots, I_{27}\}] \tag{23}$$

$$\sum_s S_{s,t,i} \leq MaxS \qquad [t \in \{Jan,\ldots,Dec\},\ i \in \{I_1, \ldots, I_{27}\}] \tag{24}$$

$$\sum_s S_{s,Dec,i} = TargetS \qquad [i \in \{I_1, \ldots, I_{27}\}] \tag{25}$$

$$S_{s,t,i} =\ S_{s,t-1,i} + F_{s,t,i} - C_{s,t,i} \qquad [s \in \{S_1,\ldots,S_8\},\ t \in \{Jan,\ldots,Dec\},\ i \in \{I_1, \ldots, I_{27}\}] \tag{26}$$

$$E_{t,i} = (FD + SD) \times \frac{WH_t}{\sum_t WH_t} \times SB_i + MFD_t \times (1 - SB_i)$$

$$[t \in \{Jan, \ldots, Dec\},\ i \in \{I_1, \ldots, I_{27}\}] \tag{27}$$

$$E_{t,i}\ \leq\ \sum_s\left(\sum_p Ratio_{s,p,t} \times HHV_{s,p,t} \times (1 - \widetilde{MC}_{s,p,t})\right) \times C_{\ s,t,i} \times (1 - QRF \times Z_{t,i})\ efficiency$$

$$[\forall \widetilde{MC}_{s,p,t} \in [25,30] \text{ and } t \in \{Jan,\ldots,Dec\},\ i \in \{I_1, \ldots, I_{27}\}] \tag{28}$$

$$F_{s,t,i}, S_{s,t,i}, C_{s,t,i}, E_{t,i} \geq 0 \qquad [s \in \{S_1, \ldots, S_8\},\ t \in \{Jan, \ldots, Dec\},\ i \in \{I_1, \ldots, I_{27}\}] \tag{29}$$

Equation 30 implies the non-anticipatively constraints related to the multi-stage stochastic programming model.

$F_{s,t,i} = F_{s,t,i'}$, $S_{s,t,i} = S_{s,t,i'}$, $C_{s,t,i} = C_{s,t,i'}$

[$s \in \{S_1, \ldots, S_8\}$, $t \in \{\text{Jan},\ldots,\text{Dec}\}$, $i, i' \in \{I_1,\ldots,I_{27}\}$ $(i \neq i')|$ t, i, i' are on the same node $n \in \{N_1, \ldots, N_{40}\}$]

(30)

Equation 30 indicates that for each node shown on the decision tree in Figure 1, the decision variables on biomass purchase, storage and consumption have to be the same for each month and the scenarios that are related to that node.

The hybrid model is also a mixed integer linear programming (MILP) model which is solved using the AIMMS software and CPLEX solver.

5. Results

Robust optimization model

The robust optimization model was solved with different ranges of $MC_{s,p,t}$ and $HHV_{s,p,t}$values to assess the variations in the solution when the uncertainty set was widened and the results are as shown in Table 3. Various ranges were utilized because a solution for all possible instances will likely be too conservative a solution. The optimum profit was achieved using the average $MC_{s,p,t}$ (30%) and average $HHV_{s,p,t}$ (8500 BTU/lb) and amounted to \$15.64 Million CAD. As the range of MC variations widens from 2% to 10%, using the average $HHV_{s,p,t}$, the optimum profit decreases from \$15.07 M to \$13.13 M. Alternatively, using the average $MC_{s,p,t}$ of 30% in the model, as the range of $HHV_{s,p,t}$ variation is expanded from 200 BTU/lb (0.12 MWh/ton) to 2000 BTU/lb (1.17 MWh/ton), the optimum profit reduces from \$15.15 M to \$13.58 M. When both parameters vary at the same time, the result becomes more conservative with more severe reduction in profit to \$11.97 M for $HHV_{s,p,t} \in$[8100 BTU/lb, 8900 BTU/lb] and $MC_{s,p,t} \in$[26%, 34%]. In the extreme ranges, the model is infeasible.

Table 3: Profit (\$ Million) for different ranges of $MC_{s,p,t}$and $HHV_{s,p,t}$ used in the robust optimization model

	$MC_{s,p,t}$ (%)

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		30(Ave.)	29-31	28-32	27-33	26-34	25-35
$HHV_{s,p,t}$	8500 (BTU/lb) (Ave.) [4.98 (MWh/ton)]	15.64	15.07	14.61	14.13	13.64	13.13
	8400-8600 (BTU/lb) [4.92-5.04 (MWh/ton)]	15.15	14.72	14.24	13.76	13.25	12.71
	8300-8700 (BTU/lb) [4.86-5.10 (MWh/ton)]	14.78	14.34	13.76	13.36	12.82	12.29
	8200-8800 (BTU/lb) [4.81-5.16 (MWh/ton)]	14.39	13.95	13.36	12.94	12.39	Infeasible
	8100-8900 (BTU/lb) [4.75-5.22 (MWh/ton)]	13.99	13.46	13.05	12.50	11.97	Infeasible
	8000-9000 (BTU/lb) [4.69-5.27 (MWh/ton)]	13.58	13.05	12.50	12.07	Infeasible	Infeasible

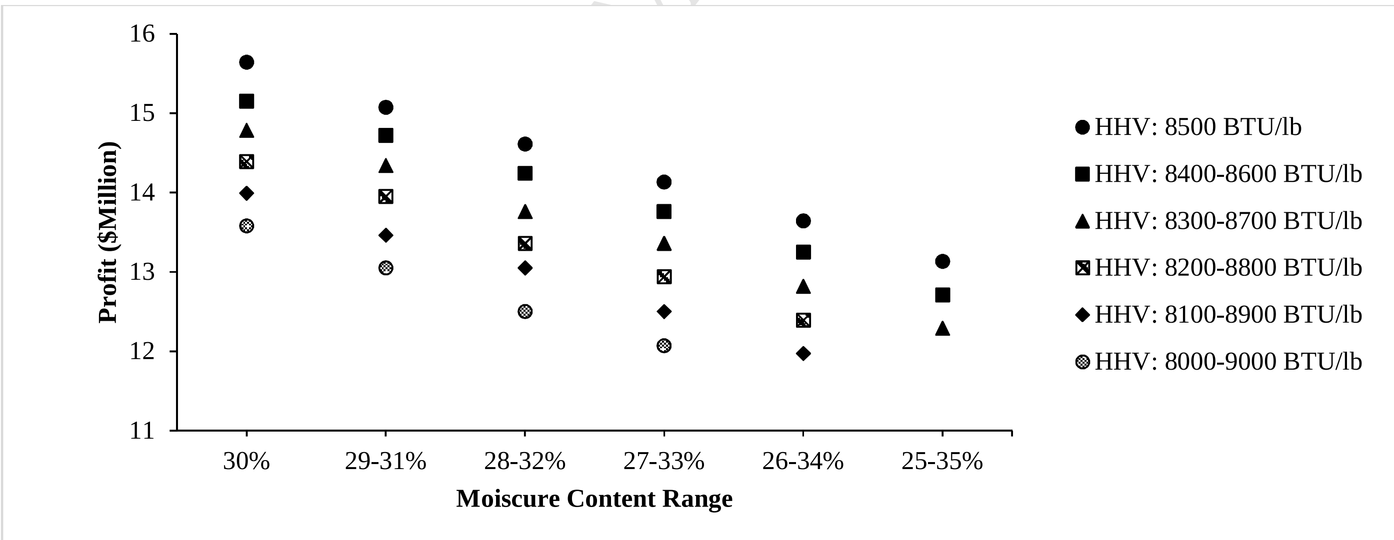

Figure 2: Solution of the robust optimization model for different ranges of moisture content and higher heating value (HHV)

Figure 2 shows the model solution (profit) for different variation ranges of $MC_{s,p,t}$ and $HHV_{s,p,t}$. Despite the conservative nature of the robust model, the decisions were feasible for ranges of

MC and HHV. Another case where the decision variables of biomass purchase, storage and consumption for the first three months were set using average MC and HHV values ($MC_{s,p,t}$=30% and $HHV_{s,p,t}$=8500 BTU/lb) is explored. For the remainder of the year, different values for MC and HHV (any ranges showed in Table 3) are modeled. It is observed that the model became infeasible when $MC_{s,p,t}$ and $HHV_{s,p,t}$ varied from their average values, a scenario that is highly likely to occur in reality.

Figures 3 and 4 show the optimum biomass storage and consumption levels in different months based on the results of the robust optimization model with $HHV_{s,p,t} \in$ [8100 BTU/lb, 8900 BTU/lb], with $MC_{s,p,t} \in$ [26%, 34%] and a deterministic model. The robust optimization model prescribes higher storage level compared to the deterministic model for most of the months and higher consumption level in all months. The consumption level was higher due to the lower than average energy value of biomass used in the robust optimization model.

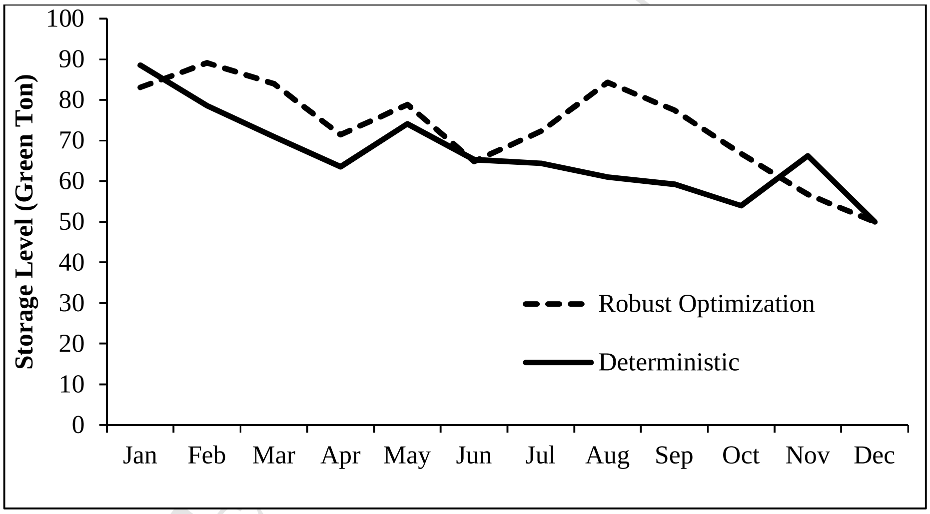

Figure 3: The optimum storage level in different months from the robust optimization model with $HHV_{s,p,t} \in$[8100 BTU/lb, 8900 BTU/lb] and $MC_{s,p,t} \in$ [26%, 34%], and the deterministic model

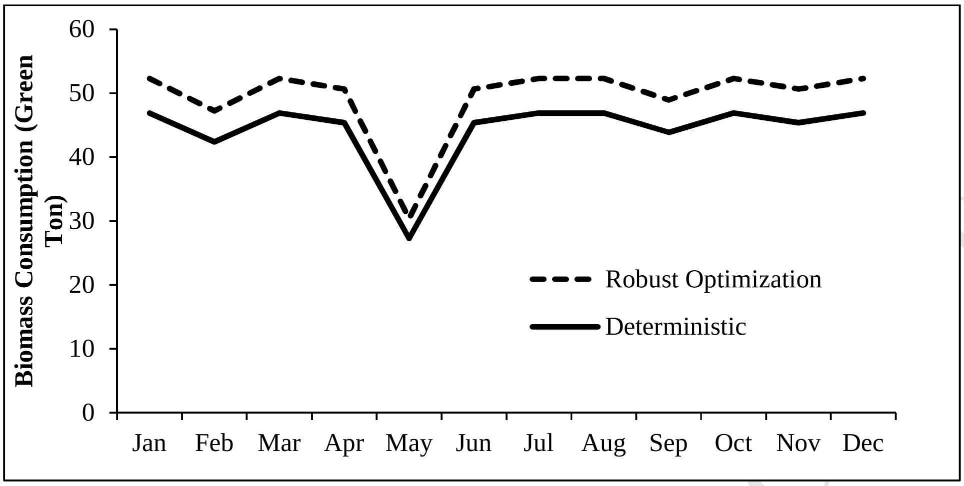

Figure 4: The optimum biomass consumption level in different months from the robust optimization model with $HHV_{s,p,t} \in$[8100 BTU/lb, 8900 BTU/lb] and $MC_{s,p,t} \in$[26%, 34%], and the deterministic model

Hybrid Model

Results of the hybrid model for three combinations of MC and HHV ranges are provided in Table 4. The profit from the hybrid model is slightly lower (0.8-1.0%) than that of the robust optimization model, suggesting more conservative tendencies of the hybrid model. The reduction in profit increases as the range of variation decreases. It should be noted that for the average values of HHV and MC, the profit is \$15.64 M for the deterministic model and \$15.33 M for the stochastic programming model. For ranges wider than $HHV_{s,p,t} \in$[8200 BTU/lb, 8800 BTU/lb] and $MC_{s,p,t} \in$[27%, 33%], the hybrid model is infeasible.

Table 4: Profit for different ranges of MC (%) and HHV (BTU/lb) used in the robust optimization and hybrid models. The final column corresponds to the 'difference' in profit predicted by the robust optimization solution (profit) versus the hybrid model.

$MC_{s,p,t}$ range (%)	$HHV_{s,p,t}$ range (BTU/lb)	Robust optimization profit($M)	Hybrid model profit ($M)	Difference ($M)
27-33	8200-8800	12.94	12.83	0.11
28-32	8300-8700	13.76	13.64	0.12
29-31	8400-8600	14.72	14.59	0.13

Despite lower profit, the hybrid model provides feasible solutions for all scenarios of monthly available biomass and all instances of MC and HHV in a selected range. It means that for variations in MC and HHV, as well as changes in the biomass availability, the hybrid model provides a solution for which the storage levels will be within the acceptable levels and the electricity demand will be met every month. This feature is crucial for the power plant considering that previous variation in biomass quality and supply resulted in production curtailment and low/ high biomass storage levels. Both extremes for storage are undesirable: high storage levels increase the risk of fire and have additional costs for the power plant and low storage levels result in low quality biomass.

In terms of the conservatism of the models, the deterministic optimization model provided a solution that had 15% higher profits than the actual planning by the power plant. Including uncertainty made the optimization model more robust, but provided consistently lower profit estimates. However, even with uncertainty included, our model predicted higher profits than what was achieved by the actual planning in the power plant. For instance, in 2011, the actual total biomass cost of the power plant was \$11.0 M. Table 5 shows the biomass purchase cost from the hybrid model for different ranges of MC and HHV, where it can be seen that only for the widest range of variations, the purchase cost is higher than \$11.0 M. More importantly, this solution is feasible for all realization within these ranges. For narrower variation ranges, the biomass purchase cost from the hybrid model is lower than the actual power plant cost, which means cost savings for the power plant, while, at the same time, preventing production curtailment and excess storage.

Table 5: Biomass purchase cost for different ranges of MC (%) and HHV (BTU/lb) used in the hybrid model

$MC_{s,p,t}$ range (%)	$HHV_{s,p,t}$ range (BTU/lb)	Hybrid model – biomass purchase cost (\$M)
27-33	8200-8800	11.4
28-32	8300-8700	10.6
29-31	8400-8600	9.7

6. Conclusions

To the best of our knowledge, this is the first study that incorporates uncertainties in biomass availability as well as biomass quality into the supply chain optimization modeling. This is achieved by developing a hybrid multi-stage stochastic-robust optimization model. Uncertainty in biomass quality was modeled using the robust optimization model, while uncertainty in biomass availability was considered using the multi-stage stochastic optimization model. The hybrid model provided consistently more conservative and more stable solutions compared to the previous deterministic model. The hybrid model yielded higher profit predictions compared to the actual power plant's real profit. At the same time, the hybrid model was solvable for all scenarios of biomass availability and all instances of biomass quality. This means that even when biomass availability and quality change during the year, the model will determine the amount of biomass to purchase, keep in storage and use in each month to maximize the annual profit, while meeting the electricity demand and preventing insufficient or excess storage levels. Our hybrid model is of utility to a forest-based biomass power-generating plant in order to optimize profits, while avoiding production curtailment and other undesirable consequences resulted from fluctuation in storage. The future research should expand the model's focus from a purely economic objective to include environmental and social aspects as well.

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Highlights:

- A robust optimization model is developed to consider uncertainty in biomass quality
- A hybrid model is developed to also include uncertainty in biomass availability
- The supply chain profit of a forest-based biomass power plant is maximized
- The robust and hybrid models provided feasible solutions considering all variations

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