1 Financial Sustainability for a Lignocellulosic Biorefinery 2 under Carbon Constraints and Price Downside Risk

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8 Abstract

9 The development of an environmentally sustainable and financially vi-
10 able replacement for fossil fuels continues to elude industry investors even
11 though the benefits of replacing them is undisputed. Biofuels are among the
12 promising replacements for fossil fuels. However, the development and pro-
13 duction process for bio-based fuels creates uncertainty for industry investors.
14 In order to increase process profitability, financial tools can be implemented
15 with current technology. This paper proposes the use of forward contracts
16 to mitigate risk, and it also considers the impact of carbon tax constraints
17 and price uncertainty. Specifically, a stochastic optimization approach is
18 implemented to develop strategies, which increases the net present value
19 (NPV) of a production facility through determination of an optimal pro-
20 duction schedule, as well as the creation of a portfolio of forward contracts
21 to reduce product price risk. Results of numerical case studies show that
22 if the policymaker is risk averse, production is higher in the early planning
23 period rather than the later period. This paper also investigates the ability
24 to maintain inventory in order to create additional financial benefit.

25 *Keywords:* Biofuels, Stochastic program, Carbon tax policies, Forward
26 contract, Financial risk

27 1. Introduction

28 Production of fuel from biomass feedstock faces uncertainty in technol-
29 ogy, logistics and market development, thus creating challenges for the in-
30 dustry investor[1]. Non-food feedstocks such as corn stover and perennial
31 grasses have the most potential to be adopted in the future generation of
32 biofuel facilities. In order to develop a viable biofuels industry, it is necessary

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33 to overcome challenges in process technology, and to determine optimal plat-
34 form design. In addition, the financial viability of the process are sufficiently
35 unstable that investment in the industry will require succinct understanding
36 of market dynamics, and careful management of financial risks. Financial
37 derivatives, such as forward and swap contracts are widely used in the en-
38 ergy industry to hedge against the price downside risk [2]. Moreover, the
39 price of biofuel based energy products does not take into account the cost
40 of greenhouse gas emissions resulting from their production [3]. National
41 governments can play a role in accomplishing a deduction of greenhouse
42 gas emission by imposing carbon emission tax [4], thereby increasing the
43 production cost of a biorefinery. According to [5], although a biorefinery
44 is generally recognized as a tax credit earning facility thanks to its green-
45 house gas emission reduction, this is not universally true due to the choice
46 of calculation criteria. As a result, it is necessary to consider the production
47 schedule under stringent carbon tax policy.

48 The main purpose of this study is to determine an optimal production
49 schedule and ethanol forward contract strategy for a biochemical lignocel-
50 lulosic biorefinery, in order to maximize its net present value under an ac-
51 ceptable level of risk. Throughout this study, the process model developed
52 in [6] is used. In addition, the forward contracts are assumed to be readily
53 available between the biorefinery and its counter-party. The forward con-
54 tracts' strike prices are determined empirically through historical spot price
55 average. The contract pricing problem is not addressed in this paper, but is
56 discussed in the future work.

57 The paper is organized as follows. Section 2 provides a literature review
58 of lignocellulosic biorefinery process optimization, the study on environmen-
59 tal and financial analysis of a lignocellulosic biorefinery, and the work on risk
60 management in energy industry. Section 3 includes the description of the
61 process parameters and assumptions, the formulation of the optimization
62 model, and the solution procedure. The results are discussed in Section 4.
63 Finally, in Section 5 the conclusions are drawn.

64 **2. Literature Review**

65 *2.1. Integrated lignocellulosic biorefinery process optimization*

66 A typical lignocellulosic biorefinery includes feedstock storage and han-
67 dling, pretreatment, saccharification and fermentation, product, water, and
68 solid recovery, as well as waste water treatment[7]. For each step, several
69 alternative technologies are available. A complete design of a biorefinery
70 process model is achieved by choosing one technology for each of these steps

71 while understanding the implications of each selection for the overall system
 72 performance. To date, researchers have proposed various methodologies to
 73 optimize the production process under specific objectives.

74 For example, Zondervan et al.[8] have established a biorefinery optimiza-
 75 tion model for a multi-product system. They consider a production network
 76 of 72 processing steps that can be used to process two different feedstocks
 77 and produce four types of products. Martin et al.[9, 10, 11] have formulated
 78 energy-optimized biorefinery conceptual models via hydrolysis and gasifica-
 79 tion of switchgrass. They postulate a superstructure that contains multiple
 80 candidate technologies in each conversion step, and formulate a mixed inte-
 81 ger nonlinear program to solve for the optimal configuration after considering
 82 both heat and water integration. Ponce-Ortega et al.[12] have proposed a
 83 disjunctive programming approach to identify the optimal biorefinery con-
 84 figuration for a given criterion (for example the economic, environmental, or
 85 safety, etc). The proposed approach enables the user to solve a difficult prob-
 86 lem through a set of easy subproblems. Ng et al.[13] have adapted a fuzzy
 87 mathematical programming approach to synthesize a sustainable integrated
 88 biorefinery that fulfills both economical and environmental considerations.
 89 Romagnoli et al. [14] develop a strategic and operational decision framework
 90 by exploiting the advantages of process simulation and hybrid optimization.
 91 Furthermore, they also fully explore the inherent nonlinearity in the con-
 92 version mechanisms of a integrated biorefinery by incorporating the kinetics
 93 of complex biological reactions in the process simulation. Floudas et al.
 94 [15] proposes the optimal configuration for a hardwood biomass to liquid
 95 transportation fuels process. The optimality of the solution is guaranteed
 96 through the use of piecewise linear underestimation of nonlinear terms and
 97 a rigorous global optimization branch-and-bound strategy. The aforemen-
 98 tioned works have only considered deterministic price for product in their
 99 formulations.

100 2.2. *Environmental and financial analysis of an integrated biorefinery*

101 Motivated by the potential of reduced greenhouse gas emission from lig-
 102 nocellulosic biorefinery facility, early studies have focused on the evaluation
 103 of life cycle greenhouse gas emission of a given facility. For example, Seabra
 104 et al. [16] conducts a life cycle analysis on a renewable jet fuel facility in
 105 Brazil with a consequential approach. They conclude the major contribu-
 106 tions to emission are feedstock production and LUC impacts. Studies such
 107 as Mullins et al. [17] also consider the uncertainty in the life-cycle analysis
 108 model. Monte Carlo simulation is applied to estimate the life cycle emission
 109 distribution of corn ethanol. They conclude the potential GHG emissions

110 reductions from biofuel is hard to forecast given the high degree uncertainty
 111 in the model. And incorporating uncertainty into decision making process
 112 enables the illumination of risk of policy failure. Later studies also include
 113 financial analysis into environmental assessment. For instance, Pereira et al.
 114 [18] have formulated both deterministic and stochastic models to determine
 115 the financial viability of producing n-butanol through two different path-
 116 ways. The results illustrate a promising revenue per tonne of sugarcane, but
 117 a discouraging internal rate of return. Moreover, Monte Carlo simulation
 118 conducted in the stochastic model shows high risk in producing n-butanol
 119 from ethanol catalysis. Pereira et al. [19] also compares the economical vi-
 120 ability of two competing process, ABE fermentation and ethanol catalysis.
 121 The results show the ABE fermentation has stronger financial performance,
 122 and n-butanol demonstrates over 50% emission reduction.

123 Although the aforementioned studies have shown the financial viabil-
 124 ity and environmental assessment are essential and sensitive to uncertainty,
 125 their major concern is not in formulating the planning and operating strate-
 126 gies for an integrated biorefinery. Moreover, compared with the price un-
 127 certainties which has the potential of swinging both upward and downward,
 128 the price downside risk is more detrimental to the financial sustainability of
 129 a lignocellulosic biorefinery [20]. Therefore, it is important to elaborate on
 130 measurement and strategies against the price risk. As a consequence, the
 131 practice of simulating uncertainties from uniform and triangular distribution
 132 becomes insufficient in terms of the temporal correlation.

133 *2.3. Current progress in financial risk management in energy industry*

134 As a result of developing markets for the product, biorefineries have
 135 been exposed to extensive price uncertainties. Thus, effective management
 136 of the financial risk arising from price fluctuations is a major concern in
 137 the industry. To date, only a few researchers have investigated this topic
 138 [21, 22, 23, 24, 25, 26, 27].

139 In the pioneering work by Bagajewicz et al.[21], a two-stage program-
 140 ming methodology has been proposed and different risk measures such as
 141 downside risk, value at risk (VaR) and conditional value at risk (cVaR)
 142 are suggested. The advantage of proposed approach is that it maintains
 143 the original MILP structure of the problem. In some later studies, finan-
 144 cial tools such as forward contracts and futures are also incorporated to
 145 hedge the risk. For example, the work by Park et al.[22] considers the fi-
 146 nancial risk management of a refinery via diversifying suppliers and futures
 147 contracts. In the work of Yun et al.[23], the authors implement futures con-
 148 tracts to hedge against the fluctuating price pattern for raw materials and

149 create a model for multi-product biorefinery to make the process more prof-
 150 itable. Recently, researchers also develop other methodologies to address
 151 the challenge in price risk. For example, Grossmann et al. [24] develops
 152 an optimization framework to address the both contract selection and price
 153 optimization with different price models. A deterministic optimization is
 154 implemented first, and then followed by a stochastic counterpart that con-
 155 sider demand and raw material price uncertainty. In their later study of
 156 the optimal procurement process in an oil refinery [25], financial deriva-
 157 tives and production flexibility strategies have been introduced in their one
 158 stage stochastic program framework. Sin et al. [27] explore the effect of
 159 market price uncertainty on the design of optimal biorefinery configuration
 160 through developing a computer-aided decision support tool. Romagnoli et
 161 al. [26] choose downside risk measure to their previous decision framework
 162 [14] to control the price uncertainty. Such choice leads to a multiobjective
 163 optimization which is solved by the ϵ constrained method.

164 The findings of these papers illustrate that the economic feasibility of bio-
 165 fuel production is tenuous and management of financial risk is essential to
 166 ensure financial sustainability. However, some of these studies use simplified
 167 linear models for the refinery/biorefinery. Thus important process details
 168 influencing the optimal production rate, and the inherent characteristic of
 169 non-linearity for process costs have been neglected [22, 23]. And among
 170 the other studies which stress the importance of process details, the man-
 171 agement of price uncertainty is achieved by adjusting certain endogenous
 172 decision variables, such as changing the optimal process configuration, feed-
 173 stock capacity and byproduct production level [27, 26]. To our knowledge,
 174 the work that strives to manage the price uncertainty through exogenous
 175 methods are Grossmann et al. [24, 25]. However, in their first study [24],
 176 the exogenous method is the determination of product's contract price [24].
 177 This is barely achievable in the case of producing bioethanol where mature
 178 market exists and each single bioethanol producer has to accept the market
 179 price regardless. In their second study [25], one of the endogenous methods
 180 is nonlinear fraction index CDU model, which is exclusively applicable to oil
 181 refinery systems. More importantly, environmental concerns, such as green-
 182 house gas (GHG) emissions are completely overlooked in the aforementioned
 183 studies. Additionally, most previous work only tends to consider price un-
 184 certainty from the supply side. The fair feedstock price for a lignocellulosic
 185 biorefinery has not yet been determined, and an efficient market for these
 186 materials has not yet developed. Therefore the estimation of price uncer-
 187 tainty is still an open concern. [28]. Whereas the markets for biofuels and
 188 bioproducts exhibit significant maturity and price volatility can be a major

189 concern.

190 As a result, the current study contributes to the state of the art by
191 considering the following aspects:

- 192 • This study considers the impact of environmental constraints the fi-
193 nancial sustainability of the modeled biorefinery. The proposed model
194 includes a tiered carbon tax constraint, determining the optimal pro-
195 duction commitment over the planning horizon.
- 196 • This study bridges the gap between sophisticated process design and
197 simplified market financial risk management by striving for a balance.
198 On the process design side, we model a lignocellulosic biorefinery from
199 [6] and obtain the optimal production commitment. On the risk man-
200 agement side, both endogenous (production scheduling) and exoge-
201 nous methods (building a forward contract portfolio) have been con-
202 sidered. Moreover, the proposed exogenous risk management methods
203 are highly related to the lignocellulosic biorefinery industry due to its
204 primary focus on product side risk.
- 205 • To our knowledge, none of the reviewed literature considers the impact
206 of inventory cost on facility's profit. The unit inventory cost is investi-
207 gated in this work and the threshold value, after which the inventory
208 policy becomes unfavorable, is assessed.

209 Therefore, it is intended that the results of this work can provide concrete
210 and feasible production and hedging recommendations to practitioners with
211 different risk preferences. More specifically, this is achieved by formulat-
212 ing a sequential stochastic program with two phases. In the first phase,
213 a detailed process model for a biochemical conversion configuration under
214 environmental constraints is built, and the most economically viable produc-
215 tion commitment is obtained. In the second phase, the model determines
216 optimal production schedule, and implements forward contracts to manage
217 risk subject to user-defined financial risk preferences.

Nomenclature

Sets

i	chemical components
j	operating unit
r	unit carbon tax price regions
l	ethanol spot price scenario index
q	month index

Parameters

M_i	molecular weight of chemical component i
Φ_i	composition of chemical component i in feedstock
T_j	required tempeature in operating unit j
Cp_i	heat capacity of chemical component i
$Price_i$	price of chemical component i
H_i	enthalpy of chemical component i
$Purindex_j$	purchasing cost index for operating unit j
a_j	installing cost multiplier for operating unit j
b_j	base price for operating unit j
$ratio_r$	upper bound ratio of greenhouse gas emission for Region r
$unit_r$	unit carbon tax price for Region r
FOC_r	process fixed operating cost corresponding to Region r
$\underline{fs}$	lower bound of the feedstock's hourly availability
cap	production capacity of the process
$Boil$	boiler efficiency
$Turbo$	Turbo generator efficiency
η	electricity surplus ratio
Tax	tax rate
IRR	internal return rate
$Time$	process lifetime
K	user defined lower bound for NPV
F_q	Forward contract price for month q
$P_{l,q}$	ethanol spot price for month q and scenario l
$P_{ethanol}$	ethanol historical mean spot price
$cost$	unit inventory cost
$\underline{S}$	lower bound for ethanol spot price of the future month
$\overline{S}$	upper bound for ethanol spot price of the future month

Variables

First stage variables

Binary variables

y_r	indicator variable, carbon emissions in region r
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Continuous variables

Mass balance variables:

$f_{i,j}$	flow of chemical component i to operating unit j
$totalC$	total amount of organic compound discharged to water

Nomenclature Cont'd

$biogas$	total amount of biogas generated for electricity generation
$genCH_4$	total amount of CH_4 generated
$genCO_2$	total amount of CO_2 generated
$genNO_x$	total amount of NO_x generated
fs	feedstock used
$prod$	the amount of ethanol produced
GHG	total amount of Greenhouse gas produced

Energy balance variables:

$Q_{h,j}$	energy needed to heat the operating unit j
$Q_{c,j}$	energy produced from operating unit j
Q_{fc}	energy produced from cooling the final product

Utility variables:

HP	High pressure steam required for heating
LP	Low pressure steam required for heating
CW	Cold water required for cooling
$electricity$	total amount of electricity generated
$steam$	total steam generated

Cost variables:

$sales$	revenue earned from ethanol and surplus electricity
VOC	variable operating cost
FCC	fixed capital cost
WC	working capital
IC	equipment installing cost
PC	equipment purchasing cost
TDC	total direct capital
TIC	total indirect capital
NI	annual netincome for the plant
NPV	net present value

Second stage variables

Continuous Variables

x_q	Production level for month q
w_q	the amount of ethanol sold in forward market for month q
c_q	the amount of ethanol sold in spot market for month q
I_q	inventory levels for month q
$carbon_tax_{l,q}$	carbon tax collected for month q and scenario l
$revenue_l$	quarterly revenue for scenario l
NI_l	quarterly netincome for scenario l
NPV_l	net present value for each scenario
α	value at risk
z_l	an auxilliary variable defined in cVaR constraint

Table 1: Conversion rate for each operating unit, based on [6]

Pretreatment	9.9% cellulose $\rightarrow$ glucose 90% hemicellulose $\rightarrow$ xylose
Hydrolysis	91.2% cellulose $\rightarrow$ glucose
Fermentation	90% organic products remain 90% remaining glucose $\rightarrow$ ethanol 80% remaining xylose $\rightarrow$ ethanol
Waste water treatment	86% organic waste $\rightarrow$ biogas
Separation	85% anhydrous ethanol is obtained and the rest is recycled

3. Methodology

3.1. Case Study and Assumptions

A biochemical conversion process typically consists of feedstock storage and handling, dilute acid pretreatment, saccharification and fermentation, product, water, and solid recovery. A schematic process diagram is shown in Figure 1. The biorefinery facility considered has an operating capacity of processing 84 tons of feedstock hourly and producing 20 tons of ethanol hourly. The process yield assumption are summarized in Table 1, based on studies of Humbird et al. [6].

Figure 1: Process Flow for Biochemical Conversion to Ethanol

In line with the assumption in [6], our research also assumes the greenhouse gas will be directly emitted and the energy collected from various operating units will heat process water to low pressure and high pressure steam for electricity generation.

Figure 2: A demonstration plot of unit carbon tax

232 In addition to the usual material, energy, capacity and financial con-
 233 straints, this paper also assumes the existence of carbon tax. Specifically,
 234 the carbon tax policy is inspired by Chen et al.[29] which explores the impact
 235 of various carbon tax levels on production and profit scales at a bioprocess-
 236 ing facility. In this work a multi-echelon model is proposed, modeled on
 237 Benjaafar et al.[30] wherein the total carbon tax increases in a piecewise lin-
 238 ear fashion as a function of the emission level, although other convex carbon
 239 tax policies are possible. This type of policy is illustrated in Figure 2

240 Note that the carbon tax region is defined by the ratio of the per unit
 241 carbon emissions and the total capacity of the process, as described in equa-
 242 tion 1.

$$ratio_r = \frac{GHG}{Cap} \quad (1)$$

243 Given the process model and carbon tax policy summarized in Section
 244 3.1, this paper considers the optimal production commitment for a quar-
 245 ter. Once the production commitment is determined, the operator faces the
 246 problem of making scheduling decisions for each month within the longer
 247 planning horizon, and encounters product price downside risk. To hedge
 248 the price downside risks, a portfolio of forward contracts is built. When
 249 modeling the above decision timeline, a stochastic program with two se-

quential phases can be formulated, in which longer term planning commitments (*prod*) are made in the first phase, and a refinement of these decisions through determination of production scheduling (x_q) and forward contract portfolio (w_q) are established in the second phase.

These two phases are further elaborated in Section 3.2 and Section 3.3 respectively.

3.2. Phase 1: Process Design and Production Planning

As previously described, the goal of the first stage model is the overall optimization of the form in Equation 2:

$$\begin{aligned} & \max_x NPV \\ & \text{subject to} \\ & f(x) = b \\ & g(x) \leq 0 \\ & x \geq 0 \end{aligned} \tag{2}$$

where the constraints for mass, energy, capacity, feedstock availability, emissions, utility and costs are given in (3)-(29). The process constraints include the mass and energy balances across all units, as well as feedstock requirements, and capacity limitations. Mass and energy balance constraints are given in (3)-(7), in which $f_{i,j}$ represents the mass flow of chemical component i in operating unit j , and Q_{h_j} , Q_{c_j} represent the heat generated/absorbed in the operating unit j . Equation 3-5 represent the material conservation for inert components, reactants and products respectively.

$$f_{i,j} = f_{i,j+1} \quad \forall i \in \text{inert} \tag{3}$$

$$f_{i,j} = f_{i,j+1}(1 - \text{conv_rate}) \quad \forall i \in \text{reactants} \tag{4}$$

$$f_{i,j} = f_{i,j+1} \cdot \text{conv_rate} \quad \forall i \in \text{products} \tag{5}$$

$$Q_{h_j} = \sum_i f_{i,j} C p_i (T_j - T_{j-1}) \tag{6}$$

$$Q_{c_j} = \sum_i f_{i,j} C p_i (T_{j+1} - T_j) \tag{7}$$

The capacity and feedstock constraints are given in equations (8) and (9), in which fs should not exceed the upper bound of feedstock and the production should not drop below the lower bound:

$$fs \geq \underline{fs} \tag{8}$$

$$\text{prod} \leq \text{cap} \tag{9}$$

270 Combustible organic byproducts separated from the process are fed to
 271 the combustor, boiler and turbogenerator system to produce steam and elec-
 272 tricity. This allows the plant to minimize energy costs, as well as providing
 273 additional revenues through generation of surplus electricity to grid. Both
 274 high pressure and low pressure steam are produced during the process to
 275 fulfill heating requirement of other operating units. Moreover, cooling wa-
 276 ter is needed to condense the remaining steam and cool down the outlet
 277 streams in some operating units. Utility constraints are summarized below
 278 in equations (10)-(14). Specifically, Equation 10 calculates the amount of
 279 high pressure steam (HP) required to heat the dilute acid pretreatment and
 280 distillation step. Equation 11 represents the amount of low pressure steam
 281 (LP) consumed to heat the boiler. Equation 12 illustrates the cold water
 282 (CW) needed for outlet steam condensation, required for many of the op-
 283 erating units in this process. Equation 13 shows the amount of the steam
 284 ($steam$) generated from the boiler equals to the total heat released from
 285 burning organic waste (mainly methane and lignin) divided by the specific
 286 enthalpy change of water. Finally, Equation 14 calculates the total watts
 287 of electricity ($electricity$) which comes from converting the heat of surplus
 288 steam in turbogenerator.

$$HP = \frac{\sum_{j=1,4} Q_{h_j}}{\Delta h_{high}} \quad (10)$$

$$LP = \frac{\sum_{j=5} Q_{h_j}}{\Delta h_{low}} \quad (11)$$

$$CW = \frac{\sum_{j=1,3,4,5,6} Q_{c_j} + Q_{fc}}{Cp_{i=H_2O}(100 - T_{amb}) + \Delta h_{water}} \quad (12)$$

$$\begin{aligned}
 steam = & \frac{Boil \cdot (genCH_4 \cdot H_{i=CH_4} + f_{i=lignin,j=3} \cdot H_{i=lignin})}{\Delta h} \\
 & + \frac{Boil \cdot (f_{i=cellu,j=3} \cdot H_{i=cellu} + f_{i=hcellu,j=3} \cdot H_{i=hcellu})}{\Delta h} \quad (13)
 \end{aligned}$$

$$electricity = \Delta H_{specific} \cdot (steam - HP - LP) \cdot Turbo \quad (14)$$

289 Two sources contribute to the greenhouse gas emissions of the process,
 290 first fermentation ($f_{i=CO_2,j=3}$) and afterwards within the waste water treat-
 291 ment, where anaerobic digestion of the organic waste ($genCO_2$) occurs.

$$GHG = genCO_2 + f_{i=CO_2,j=3} \quad (15)$$

292 To address environmental concerns, a stepwise unit carbon tax policy
 293 is used, as described in Section 3.1. Therefore, a set of binary variables

294 (y_r) is introduced to represent the carbon tax operating region decision.
 295 The upper bound for each region ($ratio_r$, see Equation (1)) is defined as
 296 the ratio of the greenhouse gas emission level to the total plant production
 297 capacity. Equation 16 represents the exclusive choice of a certain emission
 298 region the biorefinery operates on. Equation 17 calculates the total amount
 299 of greenhouse gas emission (GHG) based on the greenhouse gas emission
 300 region (GHG_r) the facility operates on. Finally, Equation 18 regulates the
 301 upper and lower bound emission level at region r .

$$\sum_{r=1}^3 y_r = 1 \quad (16)$$

$$\sum_{r=1}^3 GHG_r y_r = GHG \quad (17)$$

$$cap \cdot ratio_{r-1} \leq GHG_r \leq cap \cdot ratio_r \quad (18)$$

302 Corresponding to the stepwise unit carbon tax and capacity level, total
 303 carbon tax ($carbon_tax$) and fixed operating cost (FOC) are calculated as
 304 piecewise linear functions (see Equation 19 and Equation 20). As a result,
 305 whichever region r is selected, the total carbon tax is the sum of the tax
 306 paid for all the former regions and the surplus amount of the current region.

$$carbon_tax = \sum_{i=1}^{r-1} cap \cdot ratio_i \cdot unit_i + (GHG - cap \cdot ratio_{r-1}) unit_r y_r \quad (19)$$

307 FOC_r is the base fixed operating cost for each capacity level, while
 308 variable operating cost (VOC) is the summation of all the raw chemical
 309 components used in the process.

$$FOC = \sum_{r=1}^3 FOC_r y_r \quad (20)$$

$$VOC = \sum_i Price_i f_{i,j=1} \quad \forall i \in raw\ chemicals \quad (21)$$

310

311 Capital costs are defined below. Both purchasing capital (PC) and in-
 312 stallng capital (IC) are proportional to the material flow level in each oper-
 313 ating unit (Equation 22 and 23), and other capital costs, such as total direct
 314 cost (TDC) total indirect cost (TIC) fixed capital cost (FCC) and working
 315 capital (WC) are a function of installation costs (IC) extracted from [6] as

316 (24)-(27).

$$PC = \sum_j \text{Purindex}_j \left(\frac{\sum_i f_{i,j}}{b_j} \right)^{0.7} \quad (22)$$

$$IC = \sum_j a_j \text{Purindex}_j \left(\frac{\sum_i f_{i,j}}{b_j} \right)^{0.7} \quad (23)$$

$$TDC = 0.175ISBL + IC \quad (24)$$

$$TIC = 0.6TDC \quad (25)$$

$$FCC = TDC + TIC \quad (26)$$

$$WC = 0.1FCC \quad (27)$$

317 Finally, profit related variables include sales, net income and net present
 318 value, among which maximizing net present value is the system objective.
 319 Sales (*sales*) are the summation of revenue from selling ethanol and electric-
 320 ity. Net income (*NI*) are defined as the sales net carbon tax, fixed operating
 321 cost and variable operating cost. Finally, net present value (*NPV*) is de-
 322 fined as the summation of the present value of net income after tax and
 323 depreciation subtract fixed capital cost and working capital.

$$sales = P_{ethanol} \cdot prod + Price_{electricity} \cdot \eta \cdot electricity \quad (28)$$

$$NI = sales - carbon_tax - FOC - VOC \quad (29)$$

$$\begin{aligned} \max NPV = & \sum_{l=1}^{time} \frac{NI(1 - tax)}{(1 + IRR)^l} - FCC \\ & - WC + \sum_{l=1}^{time} \frac{(FCC + WC) \cdot tax}{time \cdot (1 + IRR)^l} \end{aligned} \quad (30)$$

324 The first phase process model calculates the quarterly production com-
 325 mitment under carbon tax constraints, while the second phase financial risk
 326 management model is presented in the next section, representing a refined
 327 decision of production commitment.

328 3.3. Phase 2: Managing Financial Risk during operation

329 In the second phase, a stochastic program is formulated with the ethanol
 330 spot price as the source of uncertainty. Sample average approximation
 331 (SAA) ([31]) is applied to generate the deterministic equivalent of such a
 332 stochastic problem. Despite some drawbacks, GBM is widely used in math-
 333 ematical finance and financial economics due to its simplicity and robustness

334 for modeling financial time series [32]. In order to ensure that the uncer-
 335 tainty is sufficiently characterized, ten thousand ethanol spot price scenarios
 336 are generated from the GBM model, which is estimated using Iowa ethanol
 337 spot price data from year 2006 to 2014[33].

338 3.3.1. Production scheduling

339 We initially consider the problem of production scheduling of each month
 340 to fulfill the commitment over the entire quarter. Therefore, the first con-
 341 straint is to fulfill the production commitment,

$$\sum_{q=1}^T x_q = prod \quad (31)$$

342 while ensuring that the production level for each month should still sat-
 343 isfy the box constraint.

$$0 \leq x_q \leq cap \quad (32)$$

344 After fulfilling the production scheduling constraints, forward contracts
 345 decisions are introduced to hedge the product price downside risk.

346 3.3.2. Forward contracts

347 In the financial industry, a forward contract is a non-standardized con-
 348 tract between two parties to buy or to sell an asset at a specified future time
 349 at a price agreed upon today [34]. Forwards, like other derivative securities,
 350 can be used to hedge risk. For this reason, ethanol produced each month
 351 (x_q) is sold via a combination of spot market (c_q) and forward contracts
 352 (w_q):

$$c_q + w_q = x_q \quad \forall q \in 1, \dots, T \quad (33)$$

353 Corresponding to the use of forward contracts, the revenue, net income
 354 and net present value under each scenario l can be redefined as follows.

$$revenue_l = \sum_{q=1}^T F_q w_q + P_{l,q} c_q \quad (34)$$

355 where the F_q represents the forward price in each month, and $P_{l,q}$ represents
 356 the ethanol spot price in each month and scenario. The net income becomes

$$NI_l = revenue_l - VOC - FOC \quad (35)$$

357 And NPV under each scenario follows by summing the net income minus
 358 capital cost plus depreciation for all the periods.

$$\begin{aligned}
 NPV_l = & \sum_{t=1}^{time} \frac{netincome_l(1 - tax)}{(1 + IRR)^t} - FCC \\
 & - WC + \sum_{t=1}^{time} \frac{(FCC + WC)tax}{time(1 + IRR)^t}
 \end{aligned} \tag{36}$$

359 3.3.3. Metrics for Risk Management

360 In the area of production economics, risk is generally defined as the
 361 potential loss due to the unexpected downfall of the product's price. Corre-
 362 spondingly, the risk preference is regarded as the maximum/minimum level
 363 of loss/profit the operator is willing to take when facing the price uncer-
 364 tainty. In the stochastic programming model, a single objective function of
 365 expected net present value is optimized. The solutions obtained are optimal
 366 on average, but risk preferences of the operators have not been considered.
 367 To explore the trade-off between different risk preference levels and optimal
 368 expected net present values, cVaR proposed by [35] is used as a risk metric.

369 Conditional value at risk (cVaR) can be regarded as the average of some
 370 percentage of the worst-case profit scenarios [36]. We choose cVaR as our
 371 risk metric as it is a coherent risk measure and can be optimized as well as
 372 constrained with convex programming methods. A given quantile $\beta \in (0, 1)$
 373 is considered along with two variables, value at risk (α) and deviation (z_l)
 374 between VaR and scenario net present value. If the net present value is less
 375 than α , z_l should be enforced to zero. The above relations can be included
 376 via the following constraints.

$$z_l < 0 \tag{37}$$

$$-\alpha + z_l + NPV_l < 0 \tag{38}$$

$$\alpha + \frac{1}{(1 - \beta)L} \sum_{l=1}^L z_l > K \tag{39}$$

377 With each of these components incorporated into the modeling frame-
 378 work, the model is solved by the solution procedure described in Section 3.4.

379 3.4. Solution Procedure

380 The overall model is comprised of first a mixed integer nonlinear pro-
 381 gram and second a stochastic linear program. Solving two phases together

can be both computationally demanding and may not result in the global optimum due to computational limitations. To overcome these difficulties, the following procedure is proposed. The first phase mixed integer nonlinear program is solved with constraints (3)-(29) and objective function (30). To further increase the solution efficiency and ensure accuracy, the mixed integer nonlinear program is decomposed to three separate nonlinear programs and solved separately by a nonlinear optimization solver CONOPT. These three convex nonlinear programs represent the optimization of achievable net present value in the corresponding carbon emission regions, and the decomposition removed the dependence on binary variables. Once the emission region with optimal objective value is selected, corresponding decision values such as production commitment (*prod*), fixed operating cost (*FOC*), variable operating cost (*VOC*), and fixed capital cost (*FCC*) are input to the second phase, in which sample average approximation (SAA) method is implemented to discretize the stochastic program into the deterministic equivalent of linear program. The linear program is solved with constraints (31)-(35),(37)-(39) and objective function (36). This procedure is illustrated in Figure 3.

The computation studies were performed on a MacBook Pro Laptop with Intel(R) Core(TM) i7-3720QM, 2.60GHz CPU, and 8GB RAM. The model was coded in GAMS 24.1.1 and the first phase decomposed MINLP model was solved with the solver CONOPT, while the second phase LP model with CPLEX 12.5.0.1.

4. Results

The goal of this approach is to develop recommendations for the production commitment, production schedule and hedging portfolio that minimize exposure to financial risk in the market. As previously described, the correlation between carbon policy and production commitment is examined through the use of a tiered carbon tax function. Whereas the results of production schedule and hedging levels are affected by risk preference levels, spot price dynamics, forward price patterns and storage capacity. Three case studies have been performed to demonstrate these relationships. In the first case, a simple forward contract is applied with constant strike price throughout the planning horizon. While in the second case, forward contracts whose strike price varies monthly are considered. Finally, in the third case, storage capacity is added on top of time-varying forward contracts. To ensure a fair comparison on optimal expected NPV, risk preference levels are maintained within the three cases.

Figure 3: Solution procedure

420 The first phase solution determines overall production commitment, byprod-
 421 uct credits and associated costs in Section 4.1. While the second phase deci-
 422 sion determines the specific production schedule and hedging policy through
 423 three case studies in Section 4.2.

424 4.1. Production Commitment: The Influence of Carbon Tax

425 The first phase optimization model determines the most economically vi-
 426 able operating commitment for the simulated bioprocess facility, constrained

Figure 4: Production commitment against Region 3 unit carbon tax shows higher carbon taxes lead to lower production commitment

Table 2: Plant decision variables for simulated biorefinery

Production commitment	Costs
Production Level	16.76 ton/h
Electricity	0.6592 GJ/(ton ethanol)
VOC	3449 \$/h
FOC	869.1 \$/h

by the overall production capacity, the greenhouse gas emissions, and production costs. Of primary importance is the determination of the impact of carbon policy on production commitments.

As shown in Figure 4 the economically efficient operating point is determined by the prices levels derived from the carbon tax policy. Once the operating regime is determined, it is always optimal to produce at the upper bound of the region. In addition, a high unit carbon tax (≥ 290 \$/ton) in Region 3 is prohibitive to full capacity production, driving a shift in operating levels from full capacity to some lower capacity level. Once the operating point is determined, the question of production scheduling and financial risk management can be addressed by the second phase optimization model. In order to examine the above two problems, we choose the unit carbon tax structure of 20\$/ton and 290\$/ton for regions 2 and 3, respectively, and the corresponding decision variables obtained from the first phase optimization are summarized in Table 2.

Figure 5: NPV distribution for case 1 $cVaR \geq 0$

Table 3: Production and financial strategy for the case 1 ($cVaR \geq 0$)

	First Month	Second Month	Third Month
production/ ton/h	13256.6	13256.6	9684.2
portion sold in forward contract market	0.336	0.336	0.218
portion sold in spot market	0	0	0.049

4.2. Refined Production Schedule and Hedging Strategy

In the second phase, the operator will determine the optimal schedule and select a portfolio of forward contracts to manage the price risk for the ethanol product, based on ten thousand scenarios to represent the price uncertainty in the ethanol market.

4.2.1. First Case: Fixed Forward Prices

In the first case, we consider the most common approach wherein the highly risk-averse operator will seek to manage production and hedging decisions to avoid losses. This behavior is formulated by setting the $cVaR$ lower bound (K) to zero, which ensures that only the lower 5% tail of the NPV distribution is below zero. The results of the first case analysis are summarized in Figure 5 and in Table 3.

As shown in Table 3, a risk-averse producer will operate at full capacity in the first two months and sell most of the product in the forward market. It is also possible to reduce the risk of operations via manipulation of the $cVaR$ lower bound (K), thereby reducing the variance of the NPV distribution as in Figure 6.

Figure 6: NPV distribution for different cVaR threshold, shows decreasing volatility with increasing cVaR constraints

Table 4: Different cVaR threshold versus objective values. Note that increasing K indicates higher risk aversion, and lower NPV

K/MM\$	E[NPV]/MM\$
-50	17.802
0	12.319
10	11.9569

459 The model reduces the financial risk by increasing the portion of the
460 product that is sold by the forward contract. This strategy reduces vari-
461 ability in product value and therefore, access to both downside and upside
462 prices are limited. As a result, overall expected NPV decreases. This trade-
463 off is illustrated in Table 4, which shows the expected NPV associated with
464 various risk levels.

465 The results presented in the first case assume that forward prices are
466 constant throughout the planning horizon of the facility. It is worthwhile
467 to relax this assumption and consider the impact of time-varying contract
468 prices.

469 4.2.2. Second Case: Time Varying Contract Prices

470 In this context, three different contract price patterns are discussed, with
471 the cVaR lower bound (K) set to zero to replicate the risk-averse decision
472 maker.

Figure 7: Production level in each month for different price pattern

473 (a) $F_1 < F_2 < F_3$ (increasing)

474 (b) $F_1 > F_2 > F_3$ (decreasing)

475 (c) $F_1 > F_2 < F_3$ (valley)

476 Using these contract price patterns, the production schedules, and the hedg-
 477 ing strategy are summarized in Figures 7, 8.

478 Examination of Figures 7 through 8 shows that the risk-averse decision
 479 maker allocates production corresponding to the forward price pattern. Pro-
 480 duction and sales are specifically maximized during the periods of highest
 481 forward prices. This allows the decision maker to simultaneously reduce risk
 482 with forward contracts, while maximizing the expected NPV of the facility.

483 4.2.3. Third Case: Allowing Inventory

484 Another strategy for managing financial risk is the use of storage to
 485 provide flexibility to the decision maker. In the initial analysis, cost of
 486 inventory is neglected. Inventory existing at the end of the planning horizon
 487 is assumed to be sold on the spot market in the subsequent month, to
 488 minimize artificial boundary effects. Risk preference level is maintained
 489 ($K=0$) and the forward contract strike prices are time varying, following the
 490 increasing pattern as previously described.

Figure 8: Portion of ethanol sold in forward market in each month for different price pattern

Therefore, Equations (33),(35) are adapted to (40)-(43) to incorporate inventory.

$$c_q + w_q + I_q = x_q + I_{q-1} \quad \forall q \in 1, \dots, T \quad (40)$$

$$I_0 = 0 \quad (41)$$

$$NI_l = revenue_l + S_0 \cdot I_T - VOC - FOC - \sum_{q=1}^T I_q \cdot cost \quad (42)$$

$$S_0 \sim U(\underline{S}, \bar{S}) \quad (43)$$

Figure 9 compares monthly production schedule with and without inventory. The production schedule decisions under time varying forward contract price, with an increasing pattern, is used here. The reverse trend of production trend shows the ability to store enables high production at low forward price period. To consider the impact of risk preferences on storage behavior, Figure 10 demonstrates the relative portion of spot market sales (blue), forward market sales (yellow), and inventory in the final period (green), with respect to decreasing risk tolerance levels. As risk tolerance decreases, uncertainty is reduced by increasing sales via forward contract. Finally, the NPV distributions derived from the three cases are compared at the same risk preference level ($K=0$) as shown in Figure 11. The increasing instances

Figure 9: Monthly production level with and without inventory, shows access to storage allows for high production level at low forward price month

in upper tail of the NPV distribution for Case 3 shows that inventory increases the likelihood of higher NPV, whereas fixed forward prices (Case 1) provide more NPV certainty with lower overall expected NPV.

Additional numerical tests support the fact that the three primary factors (forward prices, the risk preference level, and expected spot price in the future) jointly determine the inventory levels and portion sold on the spot market. While the above results only represent a policy under increasing forward price pattern and low risk preference level, various forward price and risk preference patterns can be implemented in order to generate corresponding decisions.

Finally, it is useful to consider the costs of inventory in a general way. Figure 12 shows the portion of product in inventory for each of the three months, under a range of unit inventory costs.

The important aspect of this plot is the indication that inventory costs above the threshold values of 15\$/ton will negate any benefits of allowing storage. Typical storage costs for lignocellulosic feedstock are approximately 16\$/ton [37], which is likely to be higher than the cost of storing product due to lower bulk density. It is also worth noting that the usage pattern of inventory at each month is non-uniform due to the influence from the

Figure 10: Last month product selling and inventory portion, shows that portion sold on forward contracts (yellow) increases with increase risk aversion

Figure 11: NPV distribution for different cases

Figure 12: Impact of Inventory Costs on Storage Utilization

523 expected spot price in the future and product value at the end of the time
524 horizon (S_0); thus, different inventory usage patterns would be obtained
525 with alternative future spot price expectations.

526 5. Conclusions

527 This study has introduced a stochastic sequential programming approach
528 to plan and schedule the production of a biochemical lignocellulosic biore-
529 finery while managing financial risk that arises from price uncertainty. In
530 the first phase, the biorefinery is modeled under stepwise unit carbon tax
531 constraints, based on the model introduced in [30]. First phase results in-
532 dicate a move to lower production levels is caused by a prohibitively high
533 carbon tax in Region 3 (≥ 290 \$/ton-unit).

534 Three case have been considered in the second phase. In the first case,
535 tradeoff between risk and profit has been achieved by introducing forward
536 contracts, which are effective tools in risk management. In the second case,
537 it is shown that production and hedging policy correspond to forward price
538 pattern in risk averse conditions. In the third case, it is demonstrated the
539 ability to store will weaken correlation between production schedule and for-
540 ward prices and will lead to a higher profit level. Whereas a unit inventory
541 cost of 15 \$/ton will make the inventory strategy unappealing. Moreover,
542 the use of storage and selling on the spot market decreases as the risk toler-
543 ance reduces, and the producer is driven to the price stability from forward
544 contracts.

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