ASSESSMENT OF THE FEASIBILITY OF THE PRODUCTION OF ALTERNATIVE DIESEL AND JET FUEL USING CATALYTIC HYDROTHERMOLYSIS TECHNOLOGY: A STOCHASTIC TECHNO-ECONOMIC ANALYSIS

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Abstract

The use of renewable fuels has emerged as one of the prominent methods to reduce fossil fuel consumption. Different pathway technologies can lead to different fuel products. While the feasibility of many such pathways have been analyzed with mixed results, new technologies have continuously been developed. This study uses a stochastic analysis to determine the feasibility of producing biofuels from carinata using the catalytic hydrothermolysis (CH) technology, with and without governmental incentive programs under uncertainties in input costs and governmental incentives. The study analyses a pioneer greenfield plant. The results show that the mean net present value (NPV) without governmental incentives is -$924.4 million. 90% of the simulated NPV was between -$1,040 million and -$810 million, which indicates 100% probability of loss. The mean breakeven price of jet fuel is $4.72/gal. With governmental incentives including Renewable Identification Number (RIN) and Low Carbon Fuel Standard (LCFS), the mean NPV is $62.3, and the probability of loss is reduced to 21%, which makes the process much more financially feasible.

Keywords: carinata, biofuels, techno-economic analysis, biofuel policies

1. Background

The extensive use of fossil fuels for transportation in the US is a leading contributor of air pollution, oil dependency, and the rapid depletion rate of natural resources. Decreasing the use of fossil fuels can significantly mitigate these issues. The use of renewable fuels has emerged as one of the prominent methods to achieve such a goal. In order to encourage production of biofuels and reduce fossil fuel uses, governmental programs such as Renewable Identification Number (RIN) and Low Carbon Fuel Standard (LCFS) have been implemented. Different pathway technologies can lead to different fuel products. While the feasibility of many such pathways have been analyzed with mixed results, new technologies have continuously been developed. One such technology is the catalytic hydrothermolysis (CH) process of turning carinata oil into renewable jet fuel.

Carinata oil is known as a clean source of feedstock for producing biofuels. According to Agrisoma, one of its characteristics is that it does not induce land use changes. While some crop feedstock requires new infrastructure designed exclusively to handle their conversion process, the conversion process of carinata allows producers to use existing energy infrastructure without blending[1]. Notably, carinata is among the small number of crops and the first oilseed crop to receive a sustainable certification from the Rountable on Sustainable Biofuels. As such, an analysis to determine the feasibility of producing biofuels from carinata with and without governmental incentive programs can bring some insights into the future of this crop as a feedstock for biofuels.

The catalytic hydrothermolysis process is developed by the Applied Research Associates, in partnership with Chevron Lummus Global. The process comprises three phases: catalytic hydrothermolysis phase, hydrotreating phase, and finally the fractionation phase produces the final products, which include bio-jet fuel, bio-diesel, and naphtha. It should be noted that carinata does not require hydrothermal cleanup, which is a pre-treatment step required for some other feedstock. This reduces the capital costs and operating costs of the conversion process.

There are a number of studies that examine the feasibility of producing biofuels with multiple technologies. Several studies examine the conversion of corn stover into bio-fuels using

[1] https://agrisoma.com/carinata/

pyrolysis (Anex et. al., 2010; Bittner et. al., 2015), and a few other technologies (Anex et. al, 2010). Petter and Tyner (2014) also study the conversion of biofuels from corn stover. A stochastic study of the feasibility of producing cellulosic biofuels using fast pyrolysis technology is examined by Zhao et. al. (2016). Apostolakou et. al. (2010) investigate the production of biodiesel from vegetable oils. Bann et. al. (2017) study the production of bio-jet fuel using six pathways and Monte Carlo simulations, as well as de Jong et. al. (2015), while Seber et. al. (2014) look into the production of biodiesel and bio-jet fuel from waste oils and tallows. Production of these two biofuels from fermentation technology is studied by Staples et. al. (2014). Pearlson et. al. (2013) examine the HEFA pathway using vegetable oils and animal fats. Most studies were deterministic, and none of the study has examined the feasibility of producing biofuels, including bio-jet fuel and biodiesel from the catalytic hydrothermolysis technology stochastically except for McGarvey and Tyner (2018).

McGarvey and Tyner (2018) analyze the feasibility of producing biofuel from carianata, using soybean oil as the surrogate, using the CH pathway with stochastic simulation. They found that the probability of loss is 100% without governmental incentives and as low as 74.6% with incentives. These results are based off cost data in 2015 and RIN and LCFS credits information of April 2017. However, as the conversion technology is upgraded continuously, these results may not reflect current costs accurately. Governmental incentives such as Renewable Identification Number (RIN) and Low Carbon Fuel Standard program (LCFS) also have changed sufficiently from 2017 to 2019, which may have an impact on the revenues. Their work assumes that natural gas prices correlate over time and tend to decrease, which may produce some caveats in the analysis, given (i) a sudden disruption in the price trend beginning from 2009, and (ii) the prices from 2009 and onward does not appear to show a correlation. They also assume that feedstock costs (soybean oil cost as surrogate for carinata oil) are correlated over time, and are not correlated with fuel prices, which may not precisely represent historical trends. Finally, their work utilizes a deterministic value for the RIN price, which may leave out some aspects of uncertainties, as RIN prices change continuously.

This paper aims to analyze the feasibility of the CH pathway using stochastic simulation, using the most up-to-date technical, financial data and governmental incentives information. Additionally, we construct a forecast for natural gas price based on data from 2009 onwards to better capture recent price dynamics. We also provide an alternative forecast of feedstock cost and fuel prices, in which future soybean oil prices are not correlated over time, and are correlated with future jet fuel prices, as suggested by historical trends. Finally, we model RIN price stochastically to incorporate future uncertainties. Forecast of bio-diesel and naphtha prices are based on jet fuel prices, as they are correlated with jet fuel prices.

2. Data

Financial and technical data were provided by Applied Research Association (ARA). All data were acquired in 2019. Hence, the base year for the analysis is 2018. The construction time for the plant is assumed to be three years, with production beginning in year 3 with a capacity of 50%, and 100% beginning from year 4. Similar to McGarvey and Tyner (2018), we employ a double declining depreciation method. When the annual depreciation is less than straight line depreciation, a straight line method is used for the subsequent years. Financial data details can be found in Table 1. Working capital is the capital that is used in day-to-day operations, and is assumed to be 40% of the change in operating costs from year to year. At the end of the project, working capital is assumed to be recovered by the company.

Project life total	23 years
Years of construction	3
Output	5000 bbl/day
Depreciation life	10
Debt/equity ratio	75:25%
Loan payment life	10
Working capital rate	40%
Real discount rate	10%
Nominal discount rate	12%
Inflation rate	2%
Income tax rate	16.9%

Table 1. Financial assumptions

3. Methodology

A stochastic cost-benefit analysis of the project is conducted using @Risk software. Using Monte Carlo simulation with 5000 iterations, we retrieve the distribution of net present value (NPV) of the project, and the distribution of the breakeven price (BEP) of jet fuel. The distribution of the NPV gives us the information on the specific probability of any values of the NPV. The BEP distribution allows us to understand specific BEPs that corresponds to different probabilities of loss. BEP is the selling price of jet fuel (per gallon) where NPV equals 0. At this price, the probability of loss is 50%. NPV and BEP are used in the study to determine the financial feasibility of the project. For a project to be financially viable, the NPV needs to be positive. Ideally, we lower the BEP, the more likely the project will be profitable, as it indicates that costs are low relative to revenues, and that biofuel products from the process are more likely to competitive with fossil fuel products.

The project inherently incurs risks and uncertainties. Similar to McGarvey and Tyner (2018), variables that are modeled with uncertainties include: total purchase equipment cost (TPEC), fuel conversion yield, feedstock cost, natural gas cost, fuel products prices, including bio-jet fuel, bio-diesel, and naphtha. Due to these uncertainties, values for those variables are in ranges rather than deterministic. For each iteration, a different set of input variables values is used to give a value for the NPV. Over 5000 iterations, a distribution of the NPV is gained by using different values of input variables.

4. Modeling uncertainties

4.1. Financial and technical uncertainties

4.1.1. Financial uncertainties

Total purchase equipment cost (TPEC) is the basis to calculate the total capital investment cost. Similar to McGarvey and Tyner (2018), in order to account for uncertainties in this cost item, a Pert distribution was fit. However, we use a ±25% range on the mode as the maximum and minimum values rather than ±30%, as we wish to allow for a narrower range of NPV for a more precise forecast.

4.1.2. Conversion yield

Outputs from the production process include bio-jet fuel, naphtha, and bio-diesel. We use the same conversion yield distributions as McGarvey and Tyner (2018). Jet fuel yield follows a Pert distribution (30%, 33%, 36%). Naphtha yield is fixed at 23%, and diesel yield is linearly dependent on jet yield, with a value of 69% - jet yield. These yield values remain the same over the course of project life.

4.2.Cost and product prices uncertainties

4.2.1. Natural gas cost

Natural gas is an input of the process, whose price is not constant overtime. Energy Information Administration (EIA) data shows that before 2009, natural gas price was increasing over the years, which reached its maximum value of $9.26/mcf. However, from 2009, its price has dropped significantly (see Figure 1). This is partially due to the boom in the production of shale gas in the US, beginning from 2007 *(*US Bureau of Labor Statistics, 2013)[2]. Hence, in order to follow closely the current market trend, we opt to construct a forecast for natural gas price based on the historical prices from 2009 to 2018 only.

Using the producer price index, we convert all historical prices into 2018 price. We then fit a distribution over natural gas price from 2009-2018 and choose the triangular distribution (3.257, 3.257, 6.52) for it, as it best fits the historical data, and is capped with a lower and upper bound, so that the price does not take unrealistically high or low values. The lower and upper price bounds are chosen based on the historical prices. In this timeframe, natural gas price went below $3.5/mcf only in one year (2016), and went above $5.5/mcf in only two years (2009 and 2010) . Therefore, we adjust the minimum price to $3.5/mcf and maximum price to $5.5/mcf. Even though there has been a drop since 2009, natural gas price from 2009 to 2018 does not appear to follow a trend but rather volatile and moves randomly from year to year. Hence, natural gas prices over time are not likely to correlate to each other, and the price of each year in the projection from the beginning to the end of the project is drawn randomly from the same triangular distribution to best present its volatile nature.

[2] https://www.bls.gov/opub/btn/volume-2/pdf/the-effects-of-shale-gas-production-on-natural-gas-prices.pdf

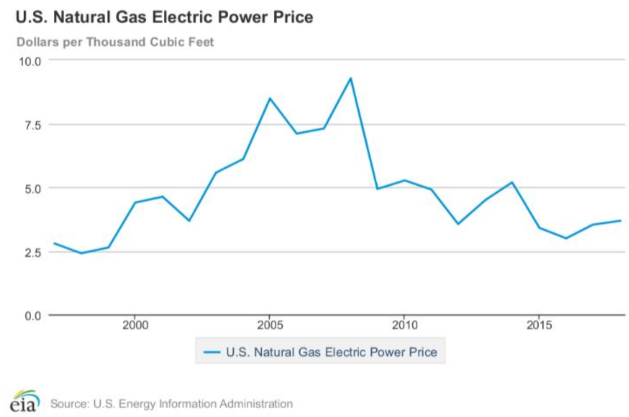


Figure 1. US historical natural gas price

Source: https://www.eia.gov/dnav/ng/hist/n3045us3m.htm

4.2.2. Forecast of carinata oil price and fuel products prices

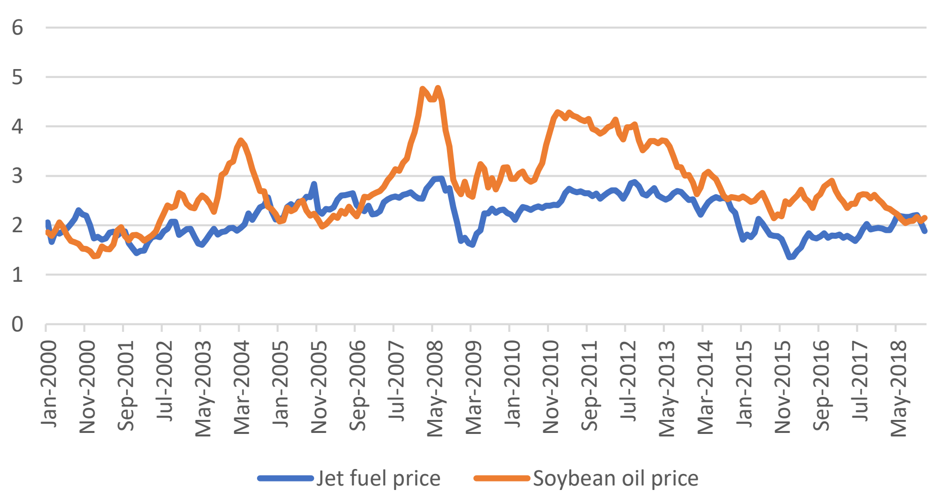
While carinata oil is the feedstock of the production process, it is a new commodity. As such, a market for carinata oil does not exist due to a lack of historical data. Thus, similar to McGarvey and Tyner (2018), we use soybean oil price as a surrogate for carinata oil price. The biofuels produced from soybean oil bears similar characteristics and quality as those produced using carinata oil, and they both can be used in similar or same facilities. Hence, if carinata is available on the market in large scale in the future, the willingness to pay for carinata of biofuel producers will not be higher than the willingness to pay for soybean oil. As such, soybean oil is chosen because its price is essentially treated as the "ceiling" price for carinata, which can give more robust results of the NPV and BEP. In order to perform the analysis, we need to construct a method to forecast the future prices of soybean oil, jet fuel, naphtha and diesel for a period of 23 years from 2018, since we assume 21 years of production, following 3 years of construction.

Forecasting future prices of soybean oil and jet fuel requires their historical prices. Monthly price data of jet fuel was collected from the EIA and was available from 1976 to 2018. Monthly price data of soybean oil was collected from the consumer report of the Illinois market available on USDA and extends from 2000 to 2018. The report includes high and low bid monthly price for soybean oil. For this analysis, we take the average price of the high and low bid. Monthly price of both soybean oil and jet fuel are converted into 2018 dollar using the consumer price index. We then compute the average annual price for soybean oil and jet fuel from the monthly price data.

In order to construct a price prediction framework, we seek to understand the nature of historical price movements and correlation of soybean oil and jet fuel. Using @Risk, We found that neither series is stationary nor having a clear trend. A stationary series is one with constant statistical properties over time[3], and a series with trend will either increase or decrease over time. Both the price data series of soybean oil and jet fuel appear to follow a random walk. The movement of jet fuel price and soybean oil over time can be found in Figure 2.

For a series with random walk, the best prediction of its future is one that follows its past patterns[4]. From Figure 2, it is apparent that although they did not appear to have a trend, historical monthly prices of soybean oil and jet fuel appear to follow each other, even though the co-movements between them is not perfectly linear[5]. In fact, the Pearson correlation between their annual prices from 2000 to 2018 is around 0.71. It means that when one price increases, the other also has a tendency to increase. A regression of soybean oil price on jet fuel price also gives a significant coefficient at 1% level, with an adjusted R-squared of 0.5.

Figure 2. Monthly historical price of jet fuel and soybean oil



[3] https://people.duke.edu/~rnau/411diff.htm
[4] https://people.duke.edu/~rnau/411rand.htm
[5] Annual price data shows the same trend, but monthly data was used for graphing for better visualization

From Figure 2, it can also be observed that historically, soybean oil price was higher than jet fuel for the majority of periods. In fact, there were 186 out of 228 months (which is equivalent to 15.5 out of 19 years) from 2000 to 2018 that soybean oil price was higher than the price of jet fuel, which is around 82% of the time. Notably, recent trend shows that soybean oil price is rarely lower than that of jet fuel. The average annual difference between soybean oil and jet fuel price from 2000-2018 is around $0.593. Hence, it indicates that predicted future prices of soybean oil should be higher than jet fuel prices for the majority of the time, with an average difference between them having a value close to $0.593. Moreover, those two forecasted prices series should be correlated to each other with a Pearson coefficient close to 0.71. Finally, the predicted prices for both series should not show clear upward or downward trends, as the historical price data shows no trend.

Even though both price series move with a random walk, there is a bound for the values that they take, since the historical correlation needs to be maintained. This is done by applying a distribution to each predicted series. A Pert distribution was chosen, as it is one of the best fits for both series, and it has a lower and upper bounds. Jet fuel price follows Pert(0.78, 2.436, 2.73), and soybean oil price follows Pert(1.48, 2.475, 5.24). As both series follow random walk, we do not use a lagged price system, as the price of next year should not be correlated to that of the current year. Thus, jet fuel and soybean price of each year is a random draw from each of their distributions. As the two series need to be correlated, we correlate annual prices of jet fuel to soybean oil prices using the correlation matrix feature in @RISK. The correlation coefficient in the matrix is set to be 0.71. The years being predicted range from 2019 to 2044.

Simulation results show that the average difference between predicted soybean oil and jet fuel price is around $0.563 for all years from 2019 to 2044, with a probability that predicted soybean oil price is higher than that of jet fuel price ranging from 85%-87% of the time. The distribution of the difference in price of a randomly picked year (in this case year 2044) can be found in Figure 3. These are desirable and realistic results, as they show very similar patterns to the historical price series, with an average difference in price close to $0.593, and a relatively low probability of price difference being negative.

Additionally, the Pearson correlation coefficient between the two predicted series has a mean of around 0.68. The distribution of the correlation coefficient of a randomly picked year can be found in Figure 4. This value is reasonably close to 0.71, which is the correlation coefficient of historical prices of soybean oil and jet fuel. Overall, the two predicted price series follow a Pert distribution with lower and upper bounds. All of these features resemble those of the historical price data. As such, we expect that this forecast is realistic, and will be used for the forecast of naphtha and diesel prices.

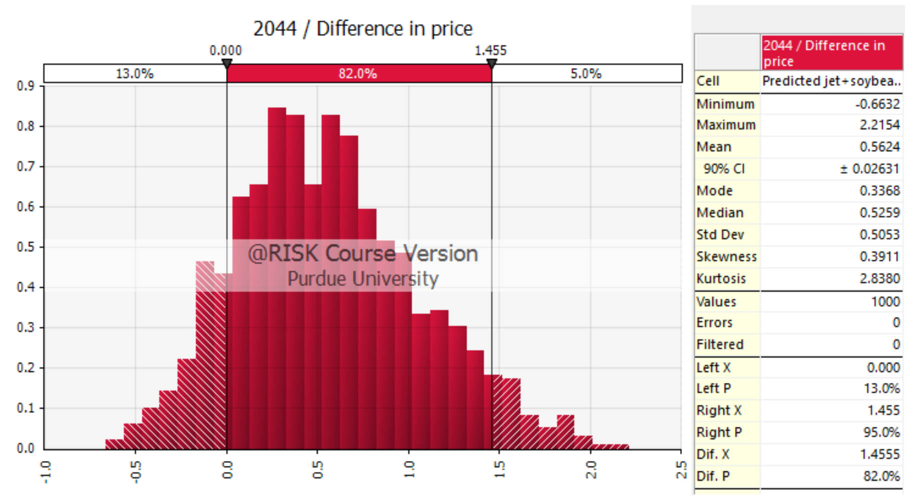


Figure 3. Distribution of difference in predicted soybean oil and jet fuel price in 2044

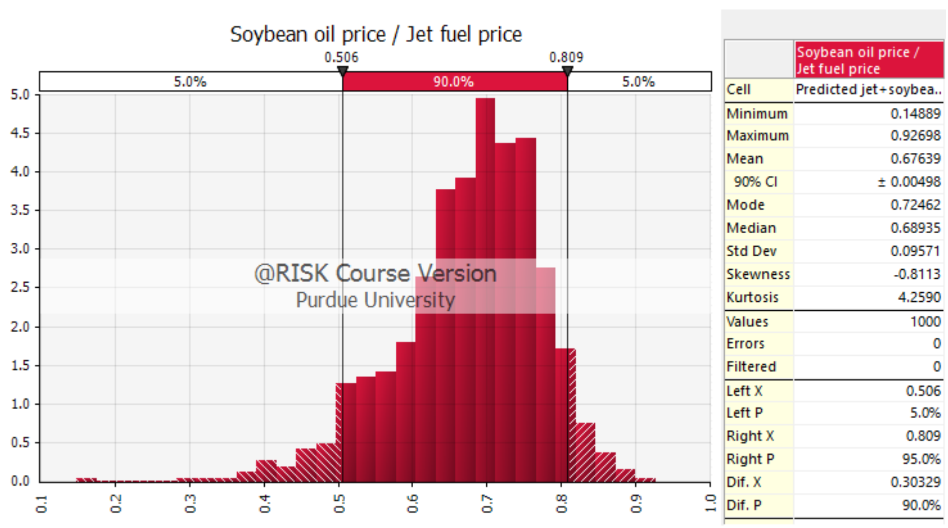


Figure 4. Distribution of correlation between predicted soybean oil and jet fuel in 2044

4.2.3. Forecast of naphtha and diesel prices

We collect historical annual wholesale diesel price data from 1995-2017 from the EIA. Gasoline price is used as a surrogate for naphtha price, as detailed and accurate historical naphtha price was not available, and was also extracted from the EIA from 1995-2017. We decide to choose to collect the prices from 1995 since fuel prices trend tend to change over time. Thus, prices of a timeframe too far away from the present may not represent well current price trends. Historical annual price movements of jet fuel, gasoline and diesel can be found in Figure 5.

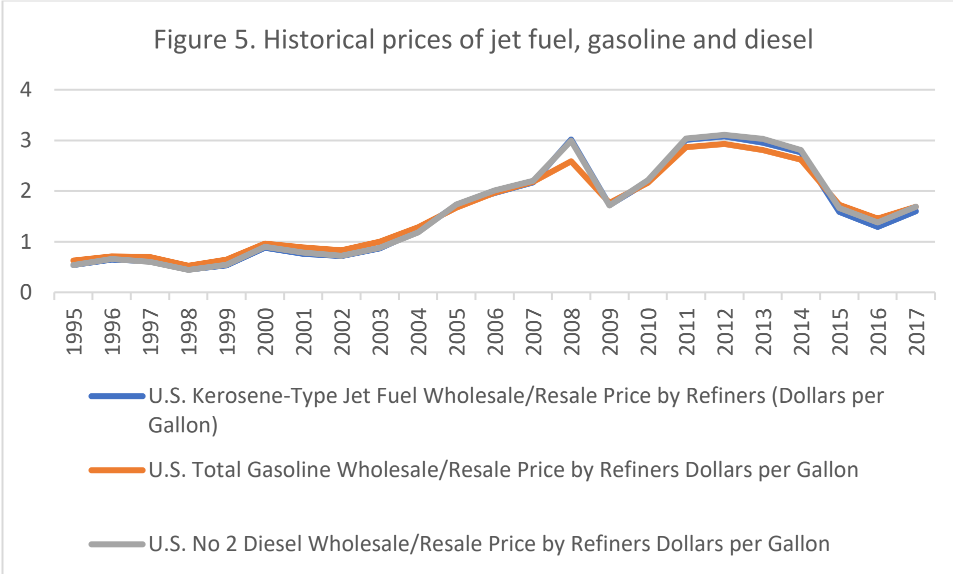
From Figure 5, we can observe that different from jet fuel and soybean oil price, prices of the three fuels follow each other very closely; and this trend has been always stable. This is partially because they all are products of crude oil, and hence follow the movements of crude oil price closely. 53% of diesel price is made up from crude oil price (EIA, 2019)[6], which may explain the close co-movements of diesel and crude oil prices. Since jet fuel and naphtha prices have the same trend as diesel, their prices follow diesel prices closely too. Thus, it is appropriate to test for a near-linear relationship between them. Gasoline is taken as a replacement for naphtha, as they are close substitutes. The relationship is reported to be:

$$Gasoline\_price_t = 0.209 + 0.876Jetfuel\_price_t \quad (1)$$

$$Diesel\_price_t = 0.0087 + 1.01jetfuel\_price_t \quad (2)$$

Both regressions (1) and (2) have an adjusted R square of 0.99, thereby suggesting a near-linear relationship between them. Since we already built a projection for jet fuel price, the relationships between diesel and gasoline with jet fuel was used to forecast the prices of gasoline and naphtha. Assuming that this relationship is stable over time, prices of diesel and gasoline in a given year will depend on the forecasted price of jet fuel in that year. Mean forecasted jet fuel price is \$2.21/gal. Biodiesel mean forecasted price is \$2.24/gal.. The mean predicted price of gasoline is \$2.14/gal.

[6] See https://www.eia.gov/energyexplained/diesel-fuel/factors-affecting-diesel-prices.php for the movement of crude oil price and diesel price, and https://www.eia.gov/energyexplained/diesel-fuel/prices-and-outlook.php for the components of diesel price

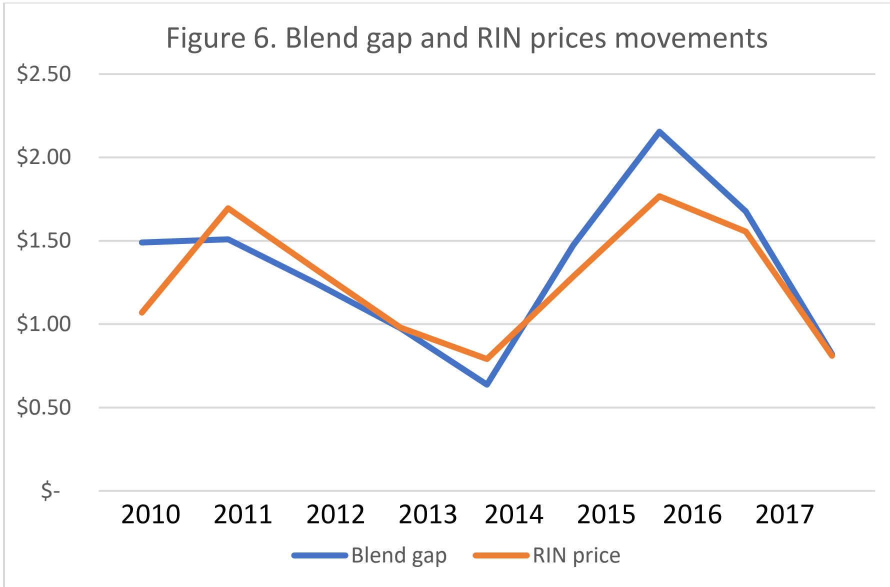


4.2.4. Forecast of RIN prices

McGarvey and Tyner (2018) use RIN price and LCFS credit of April 2017 for the analysis. In this study, we incorporate uncertainties in RIN prices and model them stochastically. Historically, RIN prices correlate strongly to the blend gap (see Figure 6). Notably, the availability of blender tax credit (BTC) in a given year may have an impact on RIN prices (Irwin et al., 2018). A BTC is believed to encourage biofuel production, thereby reducing RIN price (Markel, 2017). Therefore, historical D4 RIN prices were regressed on historical blend gap and the availability of a BTC in a given year from 2010 to 2018, yielding the relationship

$$D4\_RIN = 0.347 + 0.648 * Blend\_gap + 0.13 * BTC \qquad (3)$$

The adjusted R-squared is 0.82, indicating a good fit. The coefficient of BTC is positive. This means that with the BTC, the gap between D4 RIN price and the blend gap is larger. This supports the belief that the availability of a BTC in a year reduces the RIN prices of that year.



We then construct a forecast of the blend gap 23 years from 2018. We first obtain a forecast of fossil diesel price, based on the relationship in (2). We then forecast biodiesel prices, using forecasted soybean oil prices. Soybean oil price is the main cost component of biodiesel prices. Using the cost data of producing biodiesel from soybean oil of a representative plant from Iowa State University, we calculate the percentage of soybean oil cost in total cost of producing biodiesel to be 80%. Thus, the relationship between biodiesel prices and soybean oil prices was found to be:

$$Biodiesel\_price = 0.835 + 0.96 * soybean\_oil\_price \qquad (4)$$

The adjusted R-squared is 0.95. This relationship is then used to forecast biodiesel prices. The predicted blend gap is then obtained using forecasted fossil bio diesel prices. In order to forecast the availability of a BTC, we fit a binomial distribution on the historical data of BTC. BTC follows Bionimal(1, 0.4). With the forecasted blend gap and BTC in hand, a forecast for D4 RIN prices are obtained. Jet fuel and diesel are given D4 RIN. However, naphtha is given D5 RIN. Historically, D4, D5 and D6 RINs follow each other closely. The movements of D4 and D5 RINs can be found in Figure 7. Except for the period 2011-2013, where D4 and D5 RIN prices deviate from each other, they correlate strongly in general. Thus, in order to capture the precise trends, D5 RIN prices were regressed on D4 RIN prices for the period 2013-2018, which gives:

$$D5_RIN = 0.747 - 0.122 * D4_RIN \qquad (5)$$

The adjusted R-squared is 0.98. Using this relationship and the forecasted D4 RIN prices, a forecast for D5 RIN prices was obtained.

Figure 7. Weekly D4 and D5 RIN prices

Source: EPA, 2020 at https://www.epa.gov/fuels-registration-reporting-and-compliance-help/rin-trades-and-price-information

4.2.5. LCFS credits estimation

The LCFS program awards credits to fuels that have a carbon intensity (CI) score less than the pre-determined benchmark CI score, and penalize fuels that surpass the benchmark CI score. The CI score is given to each certified pathway. Since the CH pathway is yet to be certified, we use the average CI scores for all certified pathways that produce the same fuel products using soybean oil. This is because the CH pathway has similarities to the HEFA pathway, which uses soybean oil as one of the feedstock. Soybean oil is also the surrogate for carinata oil in our study.

Any pathway that uses soybean oil as feedstock incorporates induced land use change (ILUC) in their CI score. However, as discussed earlier, producing biofuels from carinata does not induce land use change, and hence the CI score of the CH pathway in this study is the average CI score of soybean oil pathways minus their ILUC score, giving the 26.44 as the CI score. Pre-determined benchmark CI score is set until 2030. After that, the benchmark CI score will stay at the 2030 level for a number of years. We assume the 2030 level for all the years after 2030 until the end of the project. The LCFS credits for bio-jet fuel, bio-diesel and bio-naphtha in each year are obtained using the pathway CI score and the benchmark CI score.

5. **Results**

5.1.Net present value

The distribution of the NPV of the project without RIN and LCFS for a pioneer greenfield plant can be found in Figure 8. The distribution shows that the mean NPV is negative \$924.4 million. It means that using average values of all inputs and outputs that are modelled stochastically will result in this value of NPV. The spread values of NPV in the 90% middle range is from \$-1,040 million to -\$810 million. The minimum value is around -\$1,175 million, while the maximum NPV is -\$704.9 million. These values are similar to those of McGarvey and Tyner (2018), which indicates that the process has not seen optimistic changes in profitability without RIN and LCFS after a course of 4 years[7,8]. From the distribution, we can conclude that the probability of loss is 100%. This means that without RIN and LCFS credits, the project will not make a profit in any scenario. Note that these are the results for a greenfield plant without learning curve, at a real discount rate of 10%.

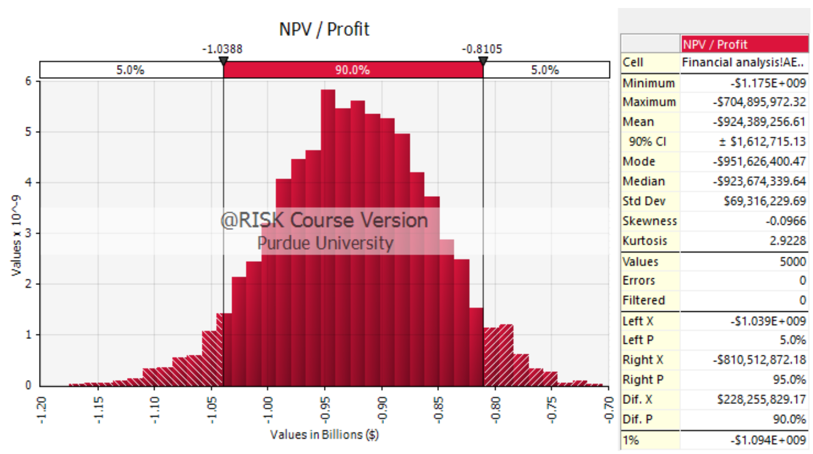


Figure 8. Distribution of NPV of the project without RIN and LCFS

The distribution of the NPV with RIN and LCFS can be found in Figure 9. The reported mean value of NPV is \$62.3 million. 90% of the simulated NPV was between -\$64 million to \$186 million. The probability of loss is 21%, which is significantly lower than the production scenario without RIN and LCFS. It suggests that governmental policies such as RIN and LCFS

[7] This study does not assume a scenario of rise in fuel prices and no learning curve

8 McGarvey and Tyner (2018) use data obtained in 2015, while this study uses data obtained in 2019.

may have significant impacts on the profitability of producing biofuels using carinata oil. These results are very much different from McGarvey and Tyner (2018), where they find that even with RIN and LCFS, the production process using carinata oil in a pioneer greenfield will not be profitable, or the probability of loss is 100%. This may be due to the differences in the modeling methods for soybean oil price and fuel prices, and RIN prices and LCFS credits, and the drastic changes of LCFS credits from 2017 to 2019[9].

The only differences in greenfield and brownfield plants is the capital investment cost. Similarly, a plant with learning curve will have lower total and operating costs than a plant without. In an n^{th} field scenario, capital investments and operating cost decrease by a reduction factor. This study does not consider these cases, but it can be inferred that with a brownfield or greenfield with learning curve (n^{th} brownfield or greenfield), the NPV may well be larger, and the probability of loss may decrease.

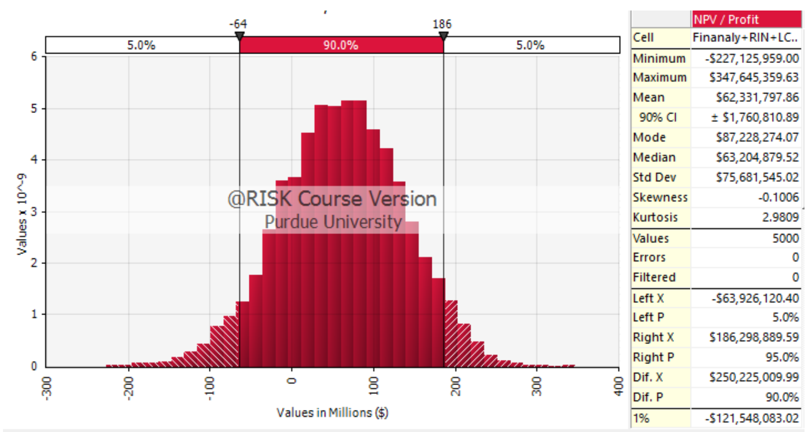


Figure 9. Distribution of NPV of the project with RIN and LCFS

5.2.<u>Break-even price</u>

Break-even price (BEP) is a price that makes NPV equals 0. The distribution of the BEP of bio-jet fuel can be found in Figure 10. The mean BEP is around \$4.72/gal. This is the price that results in a probability of loss of 50%, or the probability of earning the stipulated rate of returns of 50%. If the producer wishes to earn the stipulated rate of return with a probability of at

[9] In 2017, carbon price was 78\$/ton. From the beginning of 2019 till now, carbon price has increased to around \$200/ton and even more. See https://www.neste.com/corporate-info/investors/market-data/lcfs-credit-price

least 75%, the breakeven price of jet fuel would need to be at least \$4.86/gal. A price of at least \$5/gal will ensure earning the stipulated rate of return with a probability of 90%. The mean BEP is slightly lower than that of McGarvey and Tyner (2018), which is \$5.18/gal for a pioneer greenfield plant. This may be due to changes in technology or cost data, or modeling methods for certain inputs and outputs over time.

From section 4.2.3, mean forecasted bio-jet fuel price, biodiesel price, and gasoline (naphtha) price are \$2.21/gal, \$2.24/gal, \$2.14/gal, respectively. the RIN price is modeled stochastically with mean value \$1.2/gal for D4 RIN. Hence, mean bio-jet fuel price with RIN is \$3.41/gal. LCFS credit per gallon tend to decrease over time, depending on the pre-determined carbon intensity (CI) benchmark, which is lowered over time, and the carbon price, which is expected to stay at around \$200/MT for a number of years. LCFS credit for jet fuel is expected to range from \$1.36 to \$1.6 per gallon during the 21 years of operation, with \$1.6 being the value of the first year, before decreasing over time. Therefore, mean bio-jet fuel price with RIN and LCFS ranges from \$4.77 to \$5 per gallon with RIN and LCFS credit, with \$5 being the price in the first years, before decreasing gradually. From these results, we can see that mean bio-jet fuel prices always guarantee at least 50% probability of earning the stipulated rate of returns, even when LCFS credit decreases to the lowest value.

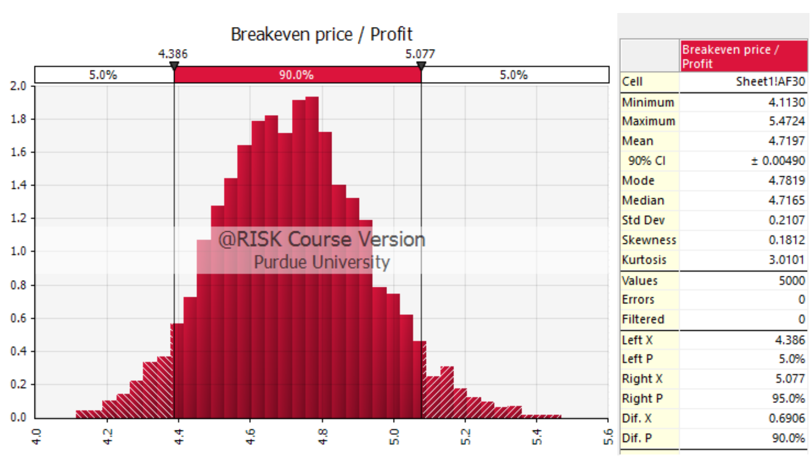


Figure 9. distribution of break-even price of bio-jet fuel

6. <u>Conclusions</u>

Relative to prior research, this techno-economic analysis uses the most up-to-date technical and financial data and governmental incentives, as well as an alternative methods of estimating LCFS credit and forecasting costs, fuel prices, and RIN values. The results show that without governmental policies, the CH pathway is not economically viable. With policies such as RIN and LCFS, the pathway becomes much more feasible. The results are based on a pioneer greenfield plant.

For a brownfield scenario, capital investment is smaller. In an n^{th} field scenario, capital investments and operating cost decrease by a reduction factor. It should be noted that uncertainties regarding soybean oil price as well as fuel prices remain, given their volatility nature and the unpredicted political environment. If sudden and/or drastic changes in those prices occur, the results of the analysis may alter. Also, there is a possibility that the RIN and LCFS programs will be abolished in the future, which may result in undesirable profitability of the production process. However, if carinata becomes a commodity with a large scale in the future, its price should not exceed soybean oil price, or it will be substituted by soybean oil. If this happens, the profitability of the process may be improved significantly, as feedstock cost is a major cost in this study and others (Pearlson et.al., 2013; McGarvey and Tyner, 2018)

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