Quantifying Breakeven Price Distributions in Stochastic Techno-Economic Analysis

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Abstract

Techno-economic analysis (TEA) is a well-established modeling process in which benefit-cost analysis (BCA) is used to evaluate the economic feasibility of emerging technologies. Most previous TEA studies focused on creating reliable cost estimates but returned deterministic net present values (NPV) and deterministic breakeven prices. The deterministic results cannot convey the considerable uncertainties embedded in techno-economic variables such as capital investment, conversion technology yield, and output prices. We obtain distributions of NPV, IRR, and breakeven price. The breakeven price is the most important indicator in TEA because it is independent of scale and communicates results effectively. The deterministic breakeven price is the price for which there is a 50 percent probability of earning more or less than the stipulated rate of return. For an investment under relatively high uncertainty, it is unlikely that investors would provide financing to a project with a 50 percent probability of loss. The point estimate breakeven price, therefore, does not represent the threshold under which investment would occur. In this study, we introduce the stochastic techno-economic analysis in which we incorporate Monte Carlo simulation into traditional TEA. A case of cellulosic biofuel production from fast pyrolysis and hydroprocessing pathway is used to illustrate the method of modeling stochastic TEA and quantifying the breakeven price distribution. The input uncertainties are translated to outputs so that the probability density distribution of both NPV and breakeven price are derived. Two methods, a mathematical method and a programming method, are developed to quantify breakeven price distribution in a way that can consider future price trend and uncertainty. We analyze two scenarios, one assuming constant real future output prices, and the other assuming that future prices follow an increasing trend with stochastic disturbances. We demonstrate that the breakeven price distributions derived

using our methods are consistent with the corresponding NPV distributions regarding the

percentile value and the probability of gain/loss.

1. Introduction

Techno-economic analysis (TEA) is a well-established modeling process, in which benefit-cost analysis (BCA) is usually used in conjunction with a fairly complete specification of the technology being evaluated. TEA has been used in evaluating emerging technologies that have not been commercialized but might achieve commercialization in the near future, such as advanced biofuel production pathways, solar photovoltaics, wind energy technologies, and carbon capture and storage technologies. Most previous TEA studies focused on creating reliable cost estimates for a given technology. They used deterministic analysis that provides point estimates and in no way communicates the uncertainty surrounding the point estimate. However, risk and uncertainty are a major impediment to investments in new technologies. Failing to communicate the levels of uncertainty does not meet the needs of potential investors or policymakers. Thus, it is important to address uncertainties in techno-economic parameters and translate them into communicable results. The major objective of this paper is to illustrate how this uncertainty analysis can be accomplished, and, in particular, how obtaining distributions of breakeven prices provides much richer information than previous approaches.

The most commonly used profitability indicators for TEA are net present value (NPV), benefit-cost ratio (B/C), internal rate of return (IRR), and return on investment (ROI). Deterministic TEAs also calculate breakeven price, which is also known as minimum selling price (MSP). Breakeven price is generally defined as the constant real fuel price through the entire production period that makes NPV equal to zero. NPV is the most popular profitability indicator. However, for emerging technologies, it is often the case that the expected NPV is negative, and the distribution is sometimes hard for investors to interpret. Also, differences in NPV across different technology pathways are difficult to compare because of differences in

scales, capital costs, etc. The IRR function often generates errors in stochastic analysis. Errors can and do occur when most of the flows are positive or negative, which is frequent with evaluation of new technologies not yet commercially viable. In contrast, the breakeven price distribution does not suffer from any of these problems. It is a unit price that is independent of scale. A higher breakeven price implies a higher unit cost and a lower possibility of profitability.

The Pacific Northwest National Laboratory (PNNL), the National Renewable Energy Laboratory (NREL) and others conducted a large number of TEA studies on advanced biofuel production pathways (de Jong et al. 2015, Jones et al. 2009, Phillips et al. 2011, Brown et al. 2013, Zhu et al. 2011). Although these studies used a breakeven price to evaluate projects, they mainly used deterministic analysis, which could not address the risks and uncertainties associated with a project. Nevertheless, risks and uncertainties associated with new technologies are both technical and economic. Common technical uncertainties are conversion efficiency, capital cost, and costs of key inputs. Economic uncertainties originate from any future prices, but in the energy arena, future fossil fuel prices are key. To account for both technical and economic uncertainties, several studies developed stochastic TEA by introducing Monte Carlo simulation into deterministic TEA. For example, Bittner, Tyner, and Zhao (2015) modeled aviation biofuel production from corn residues through fast pyrolysis. The study considered the main uncertainty parameters, such as capital investment, feedstock price, fuel yield, and oil price. They derived NPV distributions from Monte Carlo simulations. The study compared two government policies, a reverse auction and a capital subsidy, based on NPV distributions. Bauer and Hulteberg (2014) developed a probability distribution for production cost by using Monte Carlo simulation when evaluating a new thermochemical production process for isobutanol. Furthermore, based on a discounted cash flow rate of return tool, Apostolakou et al. (2009) derived ROI distributions with

respect to plant production capacity. Beyond NPV and cost distributions, some efforts were made examining the responsiveness of breakeven prices to uncertainty. For example, Reyes Valle et al. (2013) showed how MSPs respond to ±30% uncertainty in fixed capital costs. However, only a few papers attempted to extend this analysis to include a distribution of breakeven prices. Zhu et al. (2014) selected a sample size of 100 experimental cases to derive a cumulative density breakeven price distribution when evaluating a woody biomass hydrothermal liquefaction (HTL) upgrading plant. Our work suggests this sample size is too small to characterize the breakeven price distribution accurately. Abubakar, Sriramula, and Renton (2015) went a step further and developed a biodiesel probability density breakeven price distribution, but they did not present the methodology. The breakeven price is usually calculated by using numerical analysis tools such as the goal-seek function in Excel. A challenge in deriving breakeven price distribution is that standard Monte Carlo simulation cannot be performed directly in conjunction with a numerical analysis tool. Two recent studies from Yao et al. (2015) and Zhao, Brown, and Tyner (2015) developed a Macro programming method in which numerical tools were introduced in Monte Carlo simulation through programming, but future price uncertainties were not considered in the breakeven price distributions in either study.

In our experience, a distribution of breakeven prices communicates better to decision makers the potential viability and risks of a potential project than the NPV distribution. Decision makers can compare it with their beliefs about future fossil fuel prices. It allows comparison among different pathways and production scenarios. Also, the cumulative distributions can be used to perform stochastic dominance analysis. The percentile of a breakeven price in its distribution indicates the probability for private investors of achieving their stipulated rate of return. It offers policymakers guidance on the level and type of price supports that might be

needed. Therefore, it is important to develop a practical method for deriving breakeven price distribution to fill this gap in the literature.

This study illustrates two methodologies (mathematical and programming methods) for estimating breakeven price distributions based on a case study of converting corn residues to biofuels using the fast pyrolysis and hydroprocessing (FPH) pathway evaluated by Zhao, Brown, and Tyner (2015). Section 2 describes the background of the FPH biofuel production case and outlines the stochastic TEA approach. Section 3 demonstrates two methodologies of deriving breakeven price distributions. In the mathematical approach, it is possible to derive equations so that the breakeven price can actually be captured in standard Monte Carlo simulation using the @Risk add-in in Microsoft Excel (Palisade Corporation 2014). Two scenarios with different future price projections are explained in section 3.2. In the case that the base model is too complicated due to multiple correlations and tax provisions, the preferred approach to estimating a breakeven price distribution is through using a Macro programming approach as explained in section 3.3. Section 4 provides conclusions and describes applications of breakeven price distribution analysis in policy research.

2. Stochastic techno-economic analysis case study

2.1 Case study background

In this paper, we use the case of cellulosic biofuel production from a fast pyrolysis and hydroprocessing (FPH) pathway to illustrate the method of stochastic TEA and the breakeven price distribution. Fast pyrolysis is a thermal process that converts biomass into bio-oil, char, and non-condensable gas. The bio-oil produced from pyrolysis is upgraded through hydroprocessing that includes hydrotreating and hydrocracking to be blended with fossil fuels. Fig. S1 in the supplemental online material (SOM) presents a schematic depicting the FPH production

pathway. We employed the data of FPH pathway from Zhao et al. (2015) with minor modifications. That study employed a financial analysis based TEA to calculate net present values and breakeven prices. They modeled a 22-year project life plant with a size of 2,000 dry metric tons of feedstock per day (MTPD). Corn residue was used as a feedstock to produce two drop-in fuels, biogasoline, and biodiesel. Electricity was also produced as a co-product from the combustion of non-condensable gas and char. The base year was 2011. A 10-year loan was assumed with 50% debt fraction and 7.5% nominal interest rate. The inflation rate and the real discount rate used were 2.5% and 10%, respectively. Table S1 in SOM presents a summary of technical and economic assumptions. Fig. 1 shows the flow chart of net cash flows in the cellulosic biofuel production using the FPH pathway.

The previous studies incorporated uncertainty for five techno-economic variables: future fuel prices, capital cost, conversion technology yield, hydrogen cost, and feedstock cost. Pert distributions were quantified for the capital cost, hydrogen cost and feedstock cost, and a Beta general distribution was benchmarked for conversion technology yield. Geometric Brownian motion (GBM) was used to project gasoline prices. The formula is shown in equation (1):

$$P_t = P_{t-1} \times e^g + \ \varepsilon_t \tag{1}$$

where P_t is the price at period t, P_{t-1} is the price in the previous period, e is the base of the natural logarithm, and g is the expected growth rate. ε_t was the random component at period t, and ε_0 was zero since the initial price was certain $2.87/gal. (EIA 2015). A 0.27% real gasoline price growth rate from U.S. Energy Information Administration (EIA) was used. In the original study, the price change random components followed a normal distribution with a mean of zero and a standard deviation calculated from historical prices. In this study, instead of using a normal distribution for ε_t, we employ a comparable Pert distribution since the Pert distribution is

bounded so that it returns less extreme values in simulations. A Pert distribution requires parameters for the min, mode, and max values to define the distribution. A zero mode is used, and the 5th and 95th percentile values of the original normal distribution are used as the min and max in the Pert distribution. Diesel prices are projected based on historical price relationship between diesel and gasoline. In the present study, we outline the approach of modeling stochastic TEA and quantifying NPV and breakeven price distributions, but we do not address the method of quantifying input uncertainties. Hence, most of the parameters employed in the uncertain variable distributions are adapted from and documented in the previous studies (SOM Table S2). We use the mean values of uncertain distributions for the deterministic analysis.

2.2 Net present value distribution

It is important to note the difference between deterministic analysis and stochastic analysis. The deterministic analysis results in point estimations based on expected values. The stochastic analysis involves randomly sampling all the uncertain probability distributions repeatedly. In other words, for each iteration of the Monte Carlo simulation, an NPV is calculated and stored based on randomly drawn input values. Hence, the NPV distribution translates the inherent uncertainty in all the input variables into NPV uncertainty.

3. Breakeven price distribution

In the present study, a chief objective is to develop the method of quantifying breakeven price distributions. In regard to calculating a deterministic breakeven price, the common method is to employ numerical analysis tools such as the goal-seek tool in Excel, to drive NPV to zero by changing a target price. However, for quantifying the breakeven price distribution in stochastic analysis, the numerical analysis tools cannot be used directly in the Monte Carlo

simulation. In this section, we develop two methods, a mathematical method and a programming method, to quantify breakeven price distributions. Section 3.1 demonstrates the basic math of deriving breakeven price. A detailed analysis of the mathematical method is discussed using the FPH case as an example in Section 3.2. Section 3.3 explains the programming method.

3.1 Breakeven price

To approach breakeven price, we started with the NPV, which is the sum of the present value of each period:

$$NPV = \sum_{t=0}^{n} \frac{(B_t - C_t)}{(1+r)^t} \tag{2}$$

where t denotes period; n denotes the total number of periods; r denotes the real discount rate; B_t and C_t represent the total benefit and the total cost in period t, respectively.

Rearranging (2):

$$NPV = \sum_{t=0}^{n} \frac{B_t}{(1+r)^t} - \sum_{t=0}^{n} \frac{C_t}{(1+r)^t} \tag{3}$$

B_t here is the total benefit in period t of an output we target and for which the breakeven price would be derived; C_t is the total net cost, which represents the net cash flow without B_t in period t. B_t can be broken down into Q_t and P_t as the production volume and price of the output in period t. Thus,

$$NPV = \sum_{t=0}^{n} \frac{Q_t \times P_t}{(1+r)^t} - \sum_{t=0}^{n} \frac{C_t}{(1+r)^t} \tag{4}$$

Breakeven price is usually defined as the price (constant in real terms over the life of the project) that drives NPV to zero. In that sense, it is akin to the internal rate of return. When using this definition of breakeven price, future output price uncertainty would not be included in the

breakeven price distribution. In this case, assuming P_t is not correlated with C_t, by setting NPV to zero, the breakeven price P_t can be calculated.

$$P_t = \frac{\sum_{t=0}^{n} \frac{C_t}{(1+i)^t}}{\sum_{t=0}^{n} \frac{Q_t}{(1+i)^t}} \tag{5}$$

According to equation (5), the breakeven price is the ratio of net present cost (NPC) over the net present production (NPP), namely, the sum of the discounted costs divided by the sum of the discounted production volumes. It may seem strange to discount quantities, but that is necessary to get the correct timing of production matching the timing of costs. Monte Carlo simulation can be performed based on equation (5). In each iteration, uncertain input variables are sampled from input distributions, based on which a C_t and a Q_t are derived, and a breakeven price is calculated accordingly. The breakeven price distribution is the probability density distribution of all the breakeven prices calculated in the Monte Carlo simulation. Note that equation (5) assumes that P_t is not correlated with C_t. If P_t were correlated with C_t, further work would be necessary to factor out the output price, as is demonstrated using the FPH example in section 3.2. Another assumption in deriving equation (5) is that future prices are constant in real terms. In other words, the breakeven price distribution resulting from this simple construct is the constant real price with no correlations in the model and no other complications such as income taxes. More generalized cases are described in the following section.

3.2 Breakeven price distribution using the mathematical method

In the FPH pathway case, since P_t is correlated with C_t through income tax, and gasoline price is correlated with diesel price, additional derivations are necessary to derive breakeven gasoline price. Two scenarios contingent on future fuel price assumptions are analyzed. Scenario

1 assumes future fuel prices are constant in real terms. Hence, the breakeven price distribution in scenario 1 does not consider the uncertainty or trend in future prices. In scenario 2, future fuel prices are assumed to follow an unstable trajectory, the GBM fuel price projection, so that the future price trend and uncertainty become a part of the breakeven initial price distribution.

3.2.1 Scenario 1, constant future prices

For the scenario 1 analysis, the equations in Section 3.1 need some modifications. The total benefit in period t, B_t, and the total cost in period t, C_t, are in the form of net cash flows, starting with the net cash inflow in period t,

$$B_t = B_t^{gas} + B_t^{diesel} + B_t^{elec} \tag{6}$$

where B_t^{gas}, B_t^{diesel} and B_t^{elec} represent the revenue from gasoline, diesel, and electricity in period t, respectively. The capital investment, land investment, total project investment (TPI) and the initial working capital, are financed by a combination of equity and debt. Denote E_t as the equity investment in period t, LS_t as the land salvage value in period t, PMT_t as the loan repayment in period t. Also denote NWC_t as the net working capital in period t, OC_t as the operating cost in period t and T_t as tax payment in period t. Thus, the cost in period t, C_t, is:

$$C_t = E_t - LS_t + NWC_t + PMT_t + OC_t + T_t \tag{7}$$

The net benefit in period t is:

$$B_t - C_t = B_t^{gas} + B_t^{diesel} + B_t^{elec} - (E_t - LS_t + NWC_t + PMT_t + OC_t + T_t) \tag{8}$$

Denote P_t^{gas} as gasoline price in period t and Q_t^{gas} as gasoline production in period t. The gasoline price is the target for breakeven price calculation. Thus,

$$B_t^{gas} = P_t^{gas} \times Q_t^{gas} \tag{9}$$

Denote P_t^{diesel} as diesel price in period t and Q_t^{diesel} as diesel production in period t. Thus,

$$B_t^{diesel} = P_t^{diesel} \times Q_t^{diesel} \tag{10}$$

As stated above, diesel prices are assumed to be linearly correlated with gasoline prices,

$$P_t^{diesel} = \alpha P_t^{gas} + \beta \tag{11}$$

Substituting (11) into (10),

$$B_t^{diesel} = \left(\alpha P_t^{gas} + \beta\right) \times Q_t^{diesel} \tag{12}$$

Denote DEP_t as depreciation in period t, INT_t as interest payment in period t, and R_{tax} as tax rate. Thus, the tax payment, T_t, is

$$T_t = \left(B_t^{gas} + B_t^{diesel} + B_t^{elec} - OC_t - NWC_t - DEP_t - INT_t\right) \times R_{tax} \tag{13}$$

Substituting (9), (12) and (13) into (8), rearranging,

$$B_t - C_t = P_t^{gas} \times \left[\left(Q_t^{gas} + \alpha \times Q_t^{diesel}\right) \times (1 - R_{tax})\right] + \left(\beta \times Q_t^{diesel} + B_t^{elec} - OC_t - \right.$$

$$NWC_t\right) \times (1 - R_{tax}) + (DEP_t + INT_t) \times R_{tax} - (E_t - LS_t + PMT_t) \tag{14}$$

Substituting (14) into (2),

$$NPV =$$

$$\sum_{t=0}^{n} \frac{\{P_t^{gas} \times [(Q_t^{gas} + \alpha \times Q_t^{diesel}) \times (1 - R_{tax})] + (\beta \times Q_t^{diesel} + B_t^{elec} - OC_t - NWC_t) \times (1 - R_{tax}) + (DEP_t + INT_t) \times R_{tax} - (E_t - LS_t + PMT_t)\}}{(1+r)^t}$$

$$\tag{15}$$

Setting NPV to zero and rearranging we get the following equation for breakeven price,

$$P_t^{gas} = \frac{\sum_{t=0}^{n} \frac{\left[-\left(\beta \times Q_t^{diesel} + B_t^{elec} - OC_t - NWC_t\right) \times (1 - R_{tax}) - (DEP_t + INT_t) \times R_{tax} + (E_t - LS_t + PMT_t)\right]}{(1+r)^t}}{\sum_{t=0}^{n} \frac{\left[\left(Q_t^{gas} + \alpha \times Q_t^{diesel}\right) \times (1 - R_{tax})\right]}{(1+r)^t}} \tag{16}$$

Monte Carlo simulation with 10,000 iterations was conducted based on equation (16). In each iteration, a value of capital cost sampled from its distribution was returned based on which E_t, LS_t, PMT_t, INT_t and DEP_t were calculated for each period. Similarly, uncertain input distributions for conversion technology yield, hydrogen cost and feedstock cost were sampled, and Q_t^{gas}, Q_t^{diesel}, B_t^{elec}, OC_t, and WC_t were calculated in each iteration. As a result, a breakeven gasoline price, P_t^{gas}, was calculated based on the sampled and calculated values. Thus, the breakeven price distribution was generated as the probability density distribution of the 10,000 breakeven prices calculated in the simulation. The breakeven price distribution result is shown in Fig. 2A. As expected, the mean of the distribution is around the deterministic mean of $3.11/GGE. The standard deviation is $0.23/GGE. In this case, the probability of loss/gain is the probability that the breakeven price is lower/higher than the market price.

3.2.2 Scenario 2, increasing future prices with uncertainty

In the case that future prices follow an unstable trajectory, as long as future prices are projected based on the initial price, the breakeven initial price can be derived. In this scenario, we assume that future prices followed the GBM price projection described in equation (1). From GBM price projection, equation (1), P_t^{gas} can be generalized:

$$P_t^{gas} = P_0^{gas} e^{tg} + \sum_{i=0}^{t} \varepsilon_i e^{(t-i)g} \tag{17}$$

Substituting (17) into (15),

$$NPV = \sum_{t=0}^{n} \frac{\left(P_0^{gas}e^{tg} + \sum_{i=0}^{t}\varepsilon_i e^{(t-i)g}\right) \times \left[\left(Q_t^{gas} + \alpha \times Q_t^{diesel}\right) \times (1 - R_{tax})\right]}{(1+r)^t} +$$

$$\sum_{t=0}^{n} \frac{\left(\beta \times Q_t^{diesel} + B_t^{elec} - OC_t - NWC_t\right) \times (1 - R_{tax}) + (DEP_t + INT_t) \times R_{tax} - (E_t - LS_t + PMT_t)}{(1+r)^t} \qquad (18)$$

By setting NPV to zero and rearranging, P_0^{gas} can be derived.

$$P_0^{gas} =$$

$$\frac{\sum_{t=0}^{n} \frac{\left[-\sum_{i=0}^{t}\varepsilon_i e^{(t-i)g} \times \left(Q_t^{gas} + \alpha \times Q_t^{diesel}\right) \times (1 - R_{tax}) - \left(\beta \times Q_t^{diesel} + B_t^{elec} - OC_t - NWC_t\right) \times (1 - R_{tax}) - (DEP_t + INT_t) \times R_{tax} + (E_t - LS_t + PMT_t)\right]}{(1+r)^t}}{\sum_{t=0}^{n} \frac{e^{tg} \times \left[\left(Q_t^{gas} + \alpha \times Q_t^{diesel}\right) \times (1 - R_{tax})\right]}{(1+r)^t}}$$

$$(19)$$

Therefore, the initial gasoline price, P_0^{gas}, was simulated based on equation (19) through Monte Carlo simulation, and the breakeven initial price distribution was derived (presented in Fig. 2B). The mean of the distribution is \$3.04/GGE, and the standard deviation is \$0.52/GGE. Fig. 2C shows the comparison of the breakeven initial price distribution with and without future price trend and uncertainty. The breakeven initial price distribution shifts to left due to the increasing future price trend, and the distribution becomes wider because of future price uncertainty. Fig. 3A and Fig. 3B present the cumulative density distribution (CDD) of NPV and breakeven initial price, respectively. A point on the CDDs represents the probability that NPV or breakeven price is smaller than a given value of NPV or breakeven initial price. The breakeven initial price CDD was inverted since a higher breakeven price corresponds to a lower NPV. We discover that NPV distributions and breakeven price distributions are consistent in terms of percentile value and probability of gain/loss. In other words, for a given NPV in Monte Carlo simulation, there is a corresponding breakeven initial price driving the NPV to zero. Moreover,

the probability found in CDDs at the given NPV and its corresponding breakeven initial price are equal. This is verified by overlapping the NPV CDD and breakeven initial price CDD (Fig. 3C).

3.3 Breakeven price distribution using the programming method

As shown in section 3.2, the math involved in deriving a mathematical solution can become quite involved in complex cases. An alternative way to obtain a breakeven price distribution is to rely on a programming methodology. The followings are steps make use of both the @Risk add-in and Excel Macro Programming:

1) A Monte Carlo simulation with a designated number of iterations is run. All simulated values for uncertain variables returned in each iteration are saved. Uncertainties in future prices can be modeled by treating random components as members of simulation inputs. The randomly generated input values of each iteration are treated as one set of simulated values.

2) All sets of randomly simulated values are entered in the model. Each set of simulated values generates one corresponding breakeven price by applying the Excel goal-seek function.

3) Probability and cumulative density distributions can be generated based on the sample of breakeven prices. The resulting breakeven price distributions can be fit to the closest standard distribution using common statistic methods. The @Risk software performs this distribution fitting. The breakeven price at each percentile is obtained.

4) Increase the number of iterations of each simulation and repeat 1-3 steps until a smooth and convergent breakeven price distribution is derived.

Our analyses show that programming and mathematical procedure yield the same breakeven price distributions when the number of iterations is large enough. The programming method can be a way to examine the accuracy of breakeven price distributions generated by mathematical methods. The programming method to calculate the breakeven price is practical and understandable. When it comes to a complex system with multiple categories of inputs and outputs, the mathematical transformation of equations become complicated to derive. The complexity of correlations and byproducts may require intensive work to derive mathematical breakeven price expressions. For example, in Yao et al. (2015)'s techno-economic analysis of alcohol-to-jet fuel production from switchgrass and sugarcane, co-firing of the co-produced bagasse produces heat and electricity, which can be further utilized as inputs in fuel production. The excess electricity is exported to the electric grid. The purchasing and selling prices of electricity are different. In the alcohol-to-jet fuel production from corn grain case, sales of the byproducts distiller's dried grains with solubles (DDGS) generate revenues, of which the price is a function of corn prices. In these scenarios, it is not easy to transform NPV equations mathematically to derive breakeven price distributions, and the programming method is a preferred method.

On the other hand, the mathematical method is more convenient for conducting sensitivity analysis, and the programming method may be time-consuming due to the massive calculations. In general, a mathematical method is a preferred option for simple cases, and programming method is universal and is a better fit in complicated cases. The bottom line is that we have described methods that will generate breakeven price distributions for any analysis project case being evaluated.

3.4 Sensitivity analysis

The methods developed in previous sections permit analysis of measuring how sensitive is breakeven price with regard to important uncertain variables. Besides the boundary sensitivity analysis, we can perform statistic sensitivity analysis applying simulation data (Palisade Corporation 2014). Fig. 4A presents the regression coefficients from the regression of breakeven fuel price on key uncertain variables including capital investment, fuel yield, hydrogen price and feedstock cost, assuming constant future fuel prices. The number of observations equals the total number of iterations in simulations. Fig. 4B shows the sensitivity result of the mean breakeven price on input percentile of uncertain variables. Thus, both figures demonstrate how the breakeven fuel price changes as the sampled input value changes, and the results are consistent. The breakeven fuel price is most sensitive to corn residue price, followed by fuel yield and hydrogen price. Capital cost is relatively less influential than the other three variables. From this analysis, one can see that government policies that aim at reducing risks in technology conversion yield and reducing feedstock cost will help lower the breakeven price as well as enhance the probability of the FPH project.

4. Conclusions

Breakeven price is an advantageous economic indicator compared with net present value (NPV) or internal rate of return (IRR) when evaluating emerging technologies with techno-economic analysis (TEA). In this study, we highlighted the stochastic techno-economic analysis in which Monte Carlo simulation was incorporated into traditional TEA. A case of cellulosic biofuel production from fast pyrolysis and hydroprocessing (FPH) pathway was used to illustrate the methodologies for quantifying the breakeven price distributions. A breakeven price was calculated for every iteration in the Monte Carlo simulation. A mathematical method and a programming method were developed to quantify breakeven price distribution in a way that can

consider future price trend and uncertainty. We demonstrated that the breakeven price distributions derived using our methods were coherent with the corresponding NPV distributions regarding the percentile value and the probability of gain/loss.

Our experience suggests that breakeven price distributions communicate to investors and decision makers much more effectively than the typical NPV or IRR distributions, and users of the analysis can easily understand it. The distributions can be also used to conduct stochastic dominance analysis to compare projects from the perspective of risk-averse investors (Yao et al. 2015, Zhao, Brown, and Tyner 2015). In addition, breakeven price distributions are useful for conducting policy analysis. One illustration is examining the impact of length of offtake contracts on likely bid price in a reverse auction. A reverse auction is one in which the lowest qualified bidder for an offtake contract wins the contract. In prior work, it is found that the expected bid level decreases with the length of the contract because shorter contracts leave the bidder open to market price uncertainties for a longer period (Bittner, Tyner, and Zhao 2015). Reverse auctions are one policy option being considered for government procurement of advanced biofuels.

For all these reasons, we believe that including breakeven price distributions in stochastic techno-economic analysis provides a very valuable addition. In this paper, we have explained how this metric can be included in the analysis.

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References

Abubakar, Usman, Srinivas Sriramula, and Neill C. Renton. 2015. "Stochastic techno-economic considerations in biodiesel production." *Sustainable Energy Technologies and Assessments* 9:1-11. doi: http://dx.doi.org/10.1016/j.seta.2014.10.002.

Apostolakou, AA, IK Kookos, C Marazioti, and KC Angelopoulos. 2009. "Techno-economic analysis of a biodiesel production process from vegetable oils." *Fuel Processing Technology* 90 (7):1023-1031.

Bauer, Fredric, and Christian Hulteberg. 2014. "Isobutanol from glycerine – A techno-economic evaluation of a new biofuel production process." *Applied Energy* 122:261-268. doi: http://dx.doi.org/10.1016/j.apenergy.2014.02.037.

Bittner, Amanda, Wallace E. Tyner, and Xin Zhao. 2015. "Field to flight: A techno- economic analysis of the corn stover to aviation biofuels supply chain." *Biofuels, Bioproducts and Biorefining* 9 (2):201-210. doi: 10.1002/bbb.1536.

Brown, Tristan R., Rajeeva Thilakaratne, Robert C. Brown, and Guiping Hu. 2013. "Techno-economic analysis of biomass to transportation fuels and electricity via fast pyrolysis and hydroprocessing." *Fuel* 106:463-469. doi: http://dx.doi.org/10.1016/j.fuel.2012.11.029.

de Jong, Sierk, Ric Hoefnagels, André Faaij, Raphael Slade, Rebecca Mawhood, and Martin Junginger. 2015. "The feasibility of short-term production strategies for renewable jet fuels – a comprehensive techno-economic comparison." *Biofuels, Bioproducts and Biorefining* 9 (6):778-800. doi: 10.1002/bbb.1613.

EIA. 2015. "U.S. Total Gasoline Wholesale/Resale Price by Refiners." Accessed 2/5. http://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=EMA_EPM0_PWG_NUS_DPG&f=M.

Jones, Susanne B, Corinne Valkenburg, Christie W Walton, Douglas C Elliott, Johnathan E Holladay, Don J Stevens, Christopher Kinchin, and Stefan Czernik. 2009. *Production of gasoline and diesel from biomass via fast pyrolysis, hydrotreating and hydrocracking: a design case*: Pacific Northwest National Laboratory Richland, WA.

@Risk.

Phillips, Steven Dale, Joan K Tarud, Mary J Biddy, and Abhijit Dutta. 2011. Gasoline from wood via integrated gasification, synthesis, and methanol-to-gasoline technologies. National Renewable Energy Laboratory (NREL), Golden, CO.

Reyes Valle, C., A. L. Villanueva Perales, F. Vidal-Barrero, and A. Gómez-Barea. 2013. "Techno-economic assessment of biomass-to-ethanol by indirect fluidized bed gasification: Impact of reforming technologies and comparison with entrained flow gasification." *Applied Energy* 109:254-266. doi: http://dx.doi.org/10.1016/j.apenergy.2013.04.024.

Yao, Guolin, Mark D. Staples, Robert Malina, and Wallace E. Tyner. 2015.

Zhao, Xin, Tristan R. Brown, and Wallace E. Tyner. 2015. "Stochastic Techno-economic Evaluation of Cellulosic Biofuel Pathways." *Bioresource Technology* 198:755-763. doi: http://dx.doi.org/10.1016/j.biortech.2015.09.056.

Zhu, Yunhua, Mary J. Biddy, Susanne B. Jones, Douglas C. Elliott, and Andrew J. Schmidt. 2014. "Techno-economic analysis of liquid fuel production from woody biomass via hydrothermal liquefaction (HTL) and upgrading." *Applied Energy* 129:384-394. doi: http://dx.doi.org/10.1016/j.apenergy.2014.03.053.

Zhu, Yunhua, SA Tjokro Rahardjo, C Valkenburg, Lesley J Snowden-Swan, Susanne B Jones, and Michelle A Machinal. 2011. "Techno-economic Analysis for the Thermochemical Conversion of Biomass to Liquid Fuels." *Richland, Washington: Pacific Northwest National Laboratory (PNNL)*.

Fig.1 Net cash flow chart of cellulosic biofuel production using the fast pyrolysis and hydroprocessing pathway.
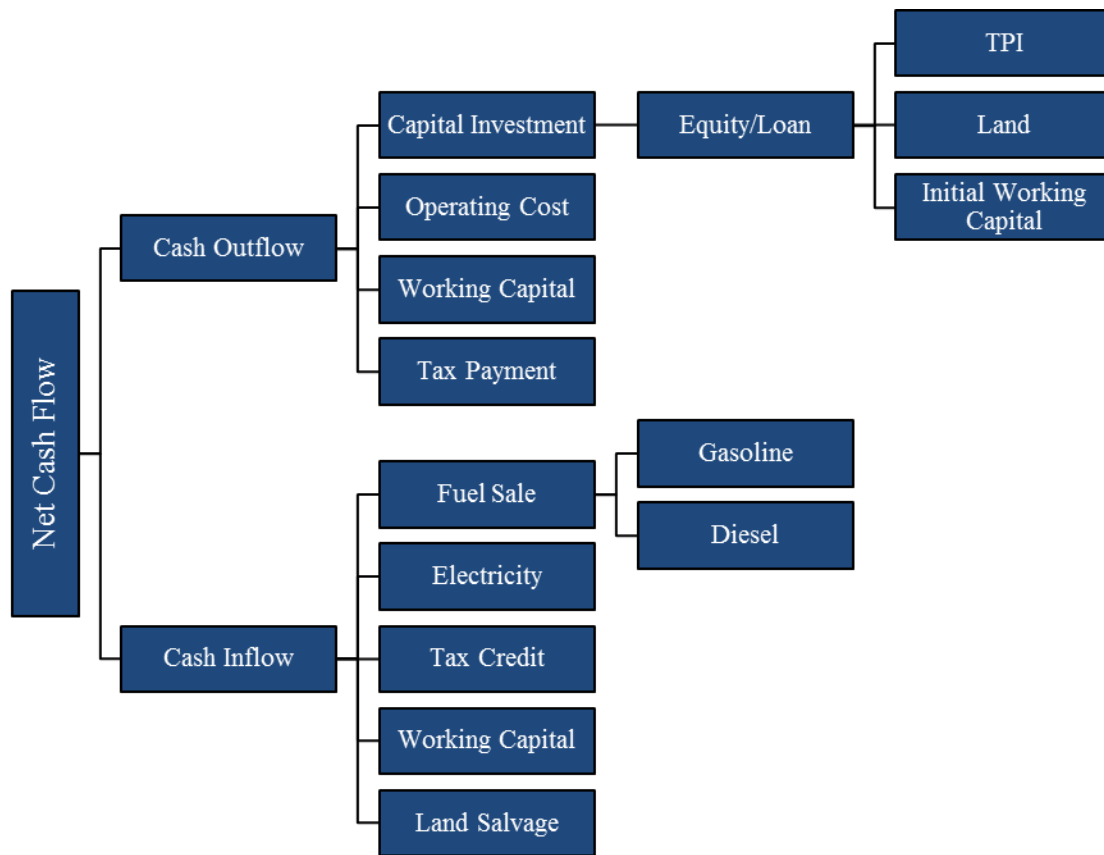
Fig. 2 Breakeven price distributions. a. The breakeven price distribution with no future price trend and uncertainty; b. the breakeven price with future price trend and uncertainty. The curves in figure a. and b. are fitted distributions. The comparison of the fitted distributions is presented in figure c.
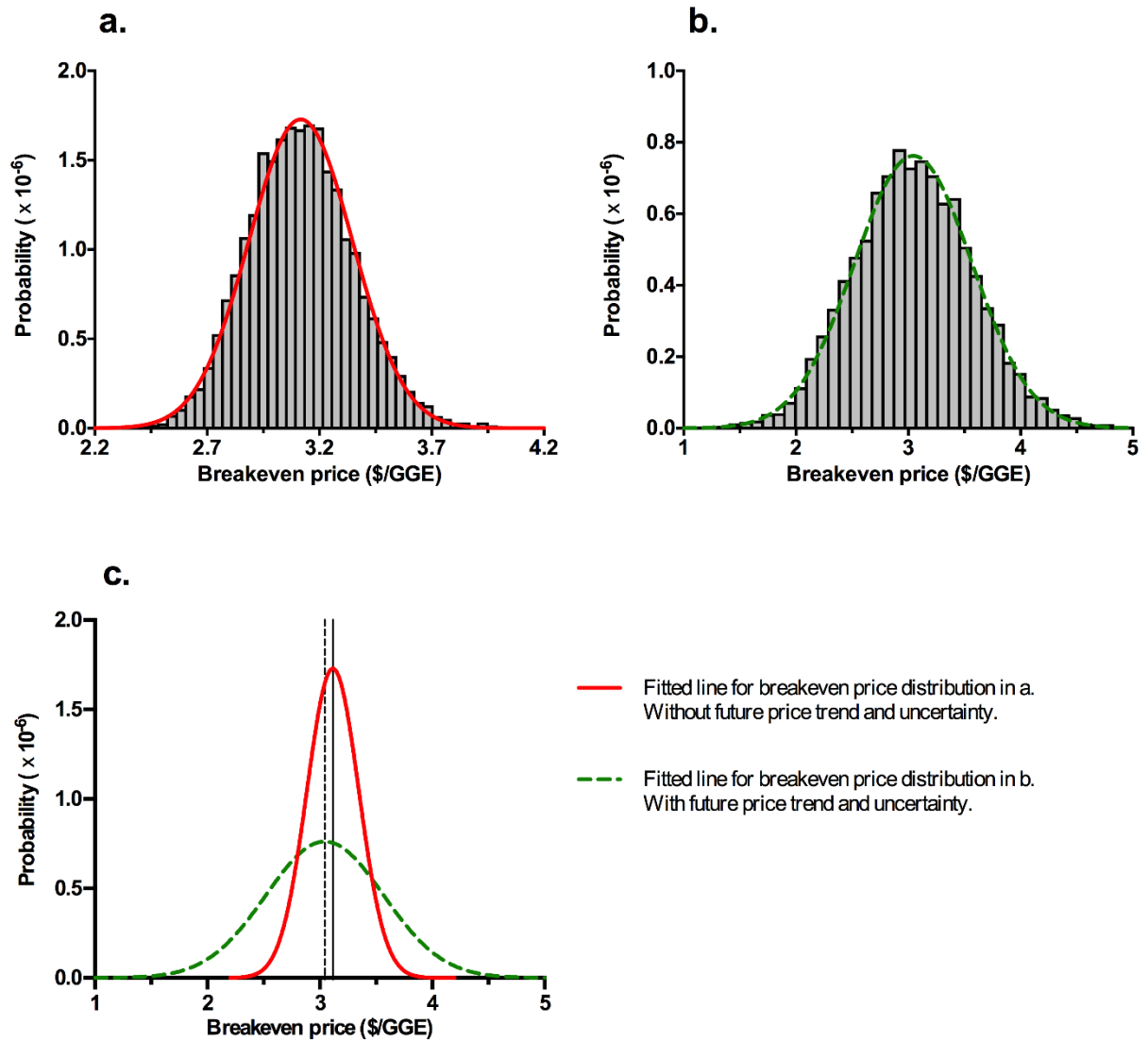
Fig. 3 Cumulative density distribution of NPV and breakeven initial price, based on all the uncertain variables. a. The NPV Cumulative density distribution; b. The breakeven initial price cumulative density distribution. c. The overlap of figures a. and b. The shaded area in figure c represents 25th to 75th percentile area.
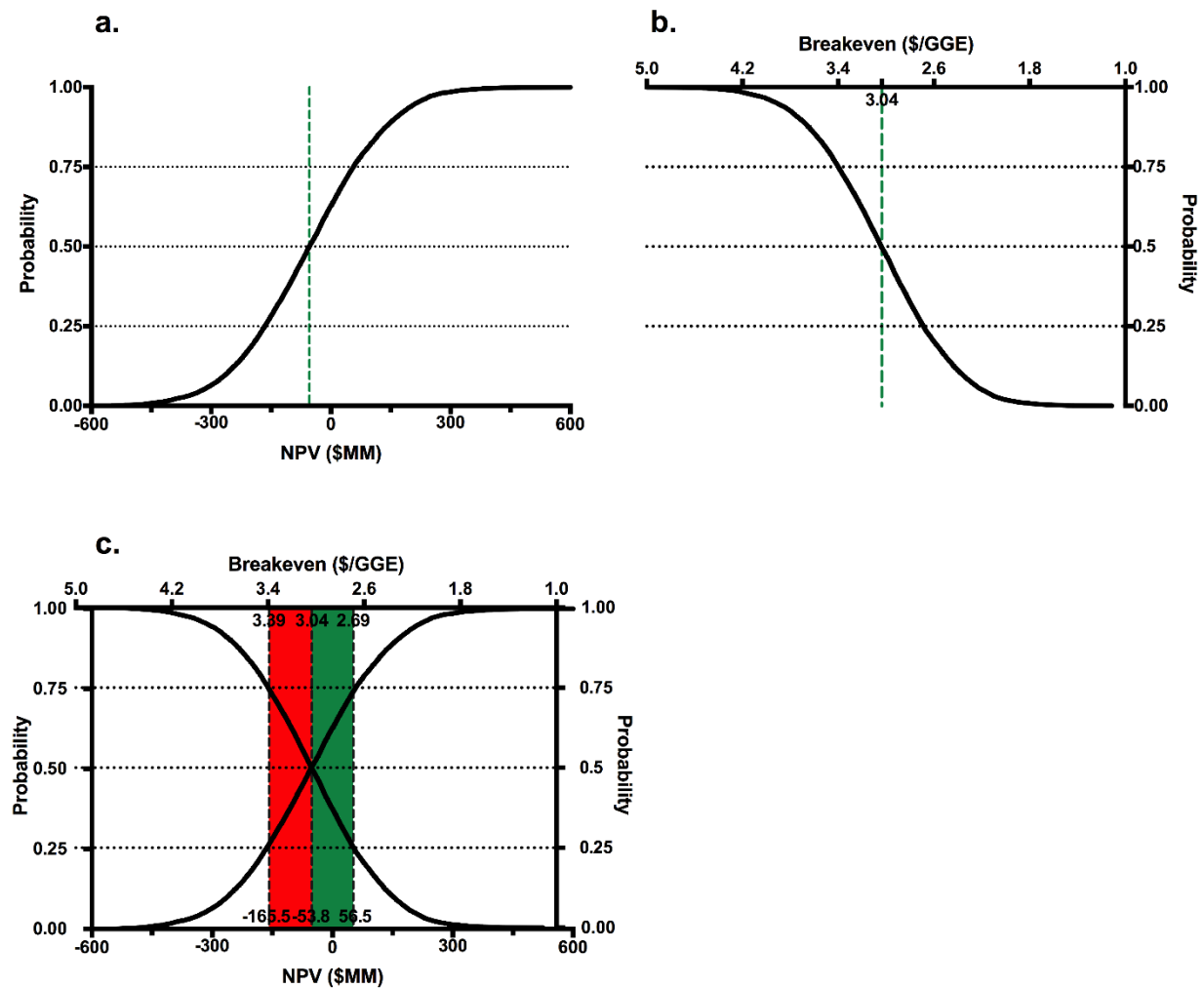
Fig. 4. Sensitivity analysis of breakeven price. a. The regression coefficient of breakeven price on uncertain variables; b. breakeven price sensitivity on input percentile of uncertain variables.