Applied Energy 183 (2016) 318–326

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

Quantifying breakeven price distributions in stochastic techno-economic analysis

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HIGHLIGHTS

- Stochastic TEA is essential for communicating the riskiness of technologies.
- The breakeven price distribution is informative and easy to communicate.
- We developed two methods to quantify breakeven price distributions in TEA.
- The methods are demonstrated using a pyrolysis biofuel pathway.
- Stochastic TEA can be used to evaluate any emerging technologies.

ARTICLE INFO

Article history:
Received 3 April 2016
Received in revised form 27 August 2016
Accepted 29 August 2016

Keywords:
Breakeven price
Techno-economic analysis
Cellulosic biofuel
Monte-Carlo simulation
Fast pyrolysis

ABSTRACT

Techno-economic analysis (TEA) is a well-established modeling process for evaluating 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 which cannot convey the considerable uncertainties embedded in important techno-economic variables. This study employs stochastic techno-economic analysis in which Monte Carlo simulation is incorporated into traditional TEA. The distributions of NPV and breakeven price are obtained. 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. Two scenarios are analyzed, one assuming constant real future output prices, and the other assuming that future prices follow an increasing trend with stochastic disturbances. It is demonstrated that the breakeven price distributions derived using the developed methods are consistent with the corresponding NPV distributions regarding the percentile value and the probability of gain/loss. The results demonstrate how breakeven price distributions communicate risks and uncertainties more effectively than NPV distributions. The stochastic TEA and the methods of creating breakeven price distribution can be applied to evaluating other technologies.

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 [1–4]. 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

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http://dx.doi.org/10.1016/j.apenergy.2016.08.184
0306-2619/

Nomenclature

Abbreviations

BCA	benefit-cost analysis
CDD	cumulative density distribution
FPH	fast pyrolysis and hydroprocessing
GBM	geometric Brownian motion
HTL	hydrothermal liquefaction
IRR	internal rate of return
MSP	minimum selling price
NPV	net present value
ROI	return on investment
TEA	techno-economic analysis

Greek abbreviations

α	coefficient in the regression of diesel prices on gasoline prices
β	intercept in the regression of diesel prices on gasoline prices
ε_t	disturbance term in geometric Brownian motion price projection ($/GGE)

Symbols

B_t^j	benefit or cash inflow from j in period t ($)
C_t	cost or cash outflow in period t ($)
DEP_t	depreciation in period t ($)
E_t	equity payment in period t ($)
g	expected real gasoline growth rate (%)
INT_t	interest payment in period t ($)
LS_t	land salvage value in period t ($)
NWC_t	net working capital in period t ($)
OC_t	operating cost in period t ($)
P_t^j	price of j in period t ($)
PMT_t	loan repayment in period t ($)
Q_t^j	production of j in period t ($)
R_{tax}	income tax rate (%)
T_t	net tax payment in period t ($)

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, internal rate of return (IRR), and return on investment (ROI). Deterministic TEA also calculates 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 [5]. 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 [1,6–12]. Although these studies used the breakeven price to evaluate projects, they mainly used deterministic analysis, which could not address the risks and uncertainties associated with a project. The deterministic breakeven price is the price for which there is about 50 percent probability of earning more or less than the stipulated rate of return. Nevertheless, it is unlikely that investors would provide financing to a project with a 50 percent probability of loss. 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 et al. [13] 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. Furthermore, Bauer and Hulteberg [14] developed a probability distribution for production cost by using Monte Carlo simulation when evaluating a new thermochemical production process for isobutanol. Apostolakou et al. [15] derived ROI distributions with respect to plant production capacity based on a discounted cash flow rate of return tool. Beyond NPV and cost distributions, some efforts were made on examining the responsiveness of breakeven prices to uncertainty. For example, Valle et al. [16] 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. [17] 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 et al. [18] went a step further and developed a biodiesel probability density breakeven price distribution, but they did not present the detailed methodology. The breakeven price is usually calculated 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. [19] and Zhao et al. [20] developed a Macro programming method in which numerical tools were introduced in Monte Carlo simulation through programming, but future price trend and 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 et al. [20]. 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 [21,22]. 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 method 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, a case of cellulosic biofuel production from a fast pyrolysis and hydroprocessing (FPH) pathway is used 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 which includes hydrotreating and hydrocracking to be blended with fossil fuels. Fig. 1 presents a schematic depicting the FPH production pathway.

This study employed the data of FPH pathway mainly from Brown et al. [1] and Zhao et al. [20] 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 2000 dry metric tons of feedstock per day. Corn residue was used as a feedstock to produce two drop-in fuels, bio-gasoline, 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 A.1 presents a summary of technical and economic assumptions. Fig. 2 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 Eq. (1):

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

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 at \$2.87/gal. A 0.27% real gasoline price growth rate from U.S. Energy Information Administration (EIA) was used [23]. 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, a comparable Pert distribution is employed since the Pert distribution is bounded so that it returns less extreme values in simulations. A Pert

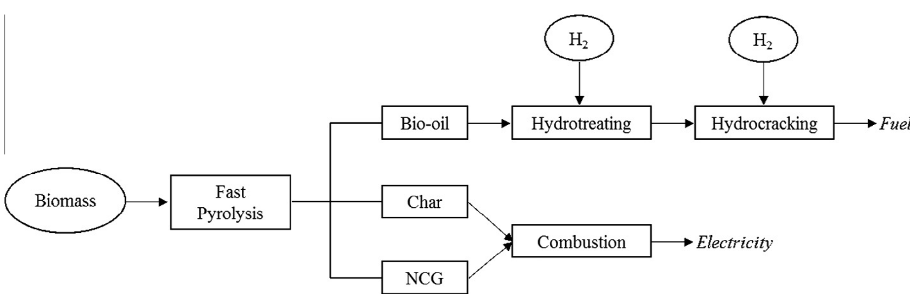

Fig. 1. Production flow chart of cellulosic biofuel production using fast pyrolysis and hydroprocessing pathway.

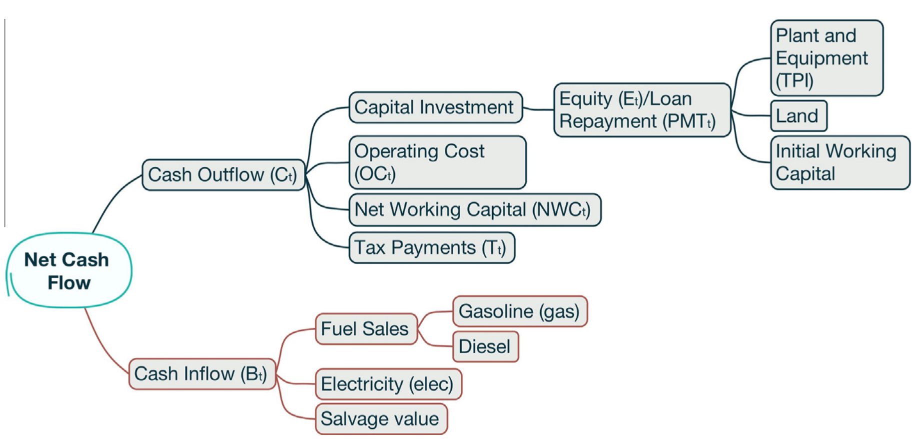

Fig. 2. Net cash flow chart of cellulosic biofuel production using the fast pyrolysis and hydroprocessing pathway.

Table 1
Parameters used in uncertain variable distributions.

Variables	Min	Mode	Max	Parameter1	Parameter2	Distribution	Mean	Source
Capital investment ($MM)	318	374	486	–	–	Pert	383.33	[20]
Corn residue cost ($/MT)	55	83	110	–	–	Pert	82.83	[13]
Hydrogen cost ($/kg)	2.25	3.25	4.25	–	–	Pert	3.25	[13]
Conversion technology yield(GGE/MT)	57.9	80.4	90.5	10.4	5.2	Beta general	79.60	[20]
ε_t in future prices ($/GGE)	−0.52	0	0.52	–	–	Pert	0	Calculated
Alpha (α)[a]							1.177	Calculated
Beta (β)[a]							−0.302	Calculated

[a] Diesel prices were regressed on gasoline price using 20-year historical data. Alpha is the coefficient and Beta is the intercept. Gasoline prices explained 99% of variances in diesel prices.

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 with linear regression. The present study highlights the approach of modeling stochastic TEA and quantifying NPV and breakeven price distributions, but it does not address the method of quantifying input uncertainties and correlations. Hence, most of the parameters employed in the uncertain variable distributions are adapted from and documented in the previous studies (Table 1). The mean values of uncertain distributions are used for the deterministic analysis.

2.2. Net present value distribution

It is important to note the difference between the deterministic analysis and the stochastic analysis. The deterministic analysis results in point estimations based on expected values, while 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 Microsoft Excel [22,24], 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, two methods, a mathematical method and a programming method, are developed 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 or plant life; 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 targeted 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,

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

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.

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

According to Eq. (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 Eq. (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 Eq. (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 Eq. (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 and co-products. 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,

$$B_t = B_t^{gas} + B_t^{diesel} + B_t^{elec} \quad (6)$$

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 including land investment, total project investment 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:

$$C_t = E_t - LS_t + NWC_t + PMT_t + OC_t + T_t \quad (7)$$

The net benefit in period t is:

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

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,

$$B_t^{gas} = P_t^{gas} \times Q_t^{gas} \quad (9)$$

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

$$B_t^{diesel} = P_t^{diesel} \times Q_t^{diesel} \quad (10)$$

As stated above, diesel prices are assumed to be linearly correlated with gasoline prices, denoting α as the coefficient and β as the intercept. Thus,

$$P_t^{diesel} = \alpha P_t^{gas} + \beta \quad (11)$$

Substituting (11) into (10)

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

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

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

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

$$\begin{aligned} B_t - C_t = {} & P_t^{gas} \times \left[(Q_t^{gas} + \alpha \times Q_t^{diesel}) \times (1 - R_{tax})\right] \\ & + (\beta \times Q_t^{diesel} + B_t^{elec} - OC_t - NWC_t) \times (1 - R_{tax}) \\ & + (DEP_t + INT_t) \times R_{tax} - (E_t - LS_t + PMT_t) \end{aligned} \quad (14)$$

Substituting (14) into (2),

$$NPV = \sum_{t=0}^{n} \frac{P_t^{gas} \times [(Q_t^{gas} + \alpha \times Q_t^{diesel}) \times (1 - R_{tax})] + (\beta \times Q_t^{diesel} + B_t^{elec} - OC_t - NWC_t) \times (1 - R_{tax}) + (DEP_t + INT_t) \times R_{tax} - (E_t - LS_t + PMT_t)}{(1+r)^t} \quad (15)$$

Setting NPV to zero and rearranging, the following equation for breakeven price is derived,

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

Monte Carlo simulation with 10,000 iterations was conducted based on Eq. (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. 3A. 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, it is assumed that future prices followed the GBM price projection described in Eq. (1). From GBM price projection, Eq. (1), P_t^{gas} can be generalized:

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

Substituting (17) into (15),

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

$$\begin{aligned} NPV = {} & \sum_{t=0}^{n} \frac{(P_0^{gas} e^{tg} + \sum_{i=0}^{t} \varepsilon_i e^{(t-i)g}) \times \left[\left(Q_t^{gas} + \alpha \times Q_t^{diesel}\right) \times (1 - R_{tax})\right]}{(1+r)^t} \\ & + \sum_{t=0}^{n} \frac{\left(\beta \times Q_t^{diesel} + B_t^{elec} - OC_t - NWC_t\right) \times (1 - R_{tax}) + (DEP_t + INT_t) \times R_{tax} - (E_t - LS_t + PMT_t)}{(1+r)^t} \end{aligned} \quad (18)$$

$$P_0^{gas} = \frac{\sum_{t=0}^{n} \frac{\left[-\sum_{i=0}^{t} \varepsilon_i e^{(t-i)g} \times \left(Q_t^{gas} + \alpha - Q_t^{diesel}\right) \times (1 - R_{tax}) - \left(\beta \times Q_t^{diesel} + B_t^{elec} - OC_t - NWC_t\right) \times (1 - R_{tax}) - (DEP_t + INT_t) \times R_{tax} + (E_t - LS_t + PMT_t)\right]}{(1+r)^t}}{\sum_{t=0}^{n} \frac{e^{tg} \times \left[\left(Q_t^{gas} + \alpha \times Q_t^{diesel}\right) \times (1 - R_{tax})\right]}{(1+r)^t}} \quad (19)$$

Therefore, the initial gasoline price, P_0^{gas}, was simulated based on Eq. (19) through Monte Carlo simulation, and the breakeven initial price distribution was derived (presented in Fig. 3B). The mean of the distribution is \$3.04/GGE, and the standard deviation is \$0.52/GGE. Fig. 3C 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. 4A and B 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. It is discovered 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. 4C.

3.3. Breakeven price distribution using the programming method

As shown in Section 3.2, the mathematics 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 [21] and Microsoft Excel Macro Programming [22], but note that any software or programming that can perform Monte Carlo simulation and numerical analysis can be used:

1. Define uncertain variable distributions and correlations. The programming method uses the same set of uncertain variables as in the mathematical method.
2. Run a Monte Carlo simulation with a designated number of iterations. 10,000 iterations were used in this study as a rule of thumb ensuring convergence for small models, but the number of iterations may depend on the number of uncertain variables and sampling method [25].
3. Save all simulated values for uncertain variables returned in each iteration. 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. 10,000 sets of simulated data are generated.
4. Enter all sets of randomly simulated values in the model. Each set of simulated values generates one corresponding breakeven price by applying the Microsoft Excel goal-seek function [24]. Thus, 10,000 breakeven prices are calculated.
5. Probability and cumulative density distributions can be generated based on the calculated samples of breakeven prices. The

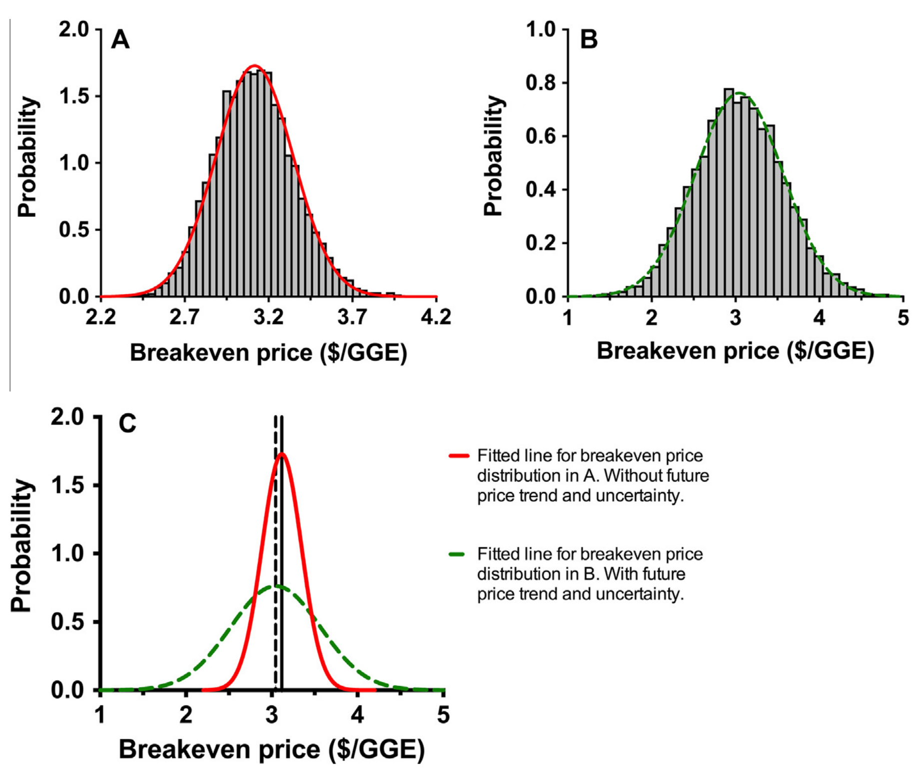

Fig. 3. Breakeven price distributions. (A) The breakeven price distribution with no future price trend and uncertainty; (B) the breakeven price with future price trend and uncertainty. The curves in figure A and B are fitted distributions. The comparison of the fitted distributions is presented in figure (C).

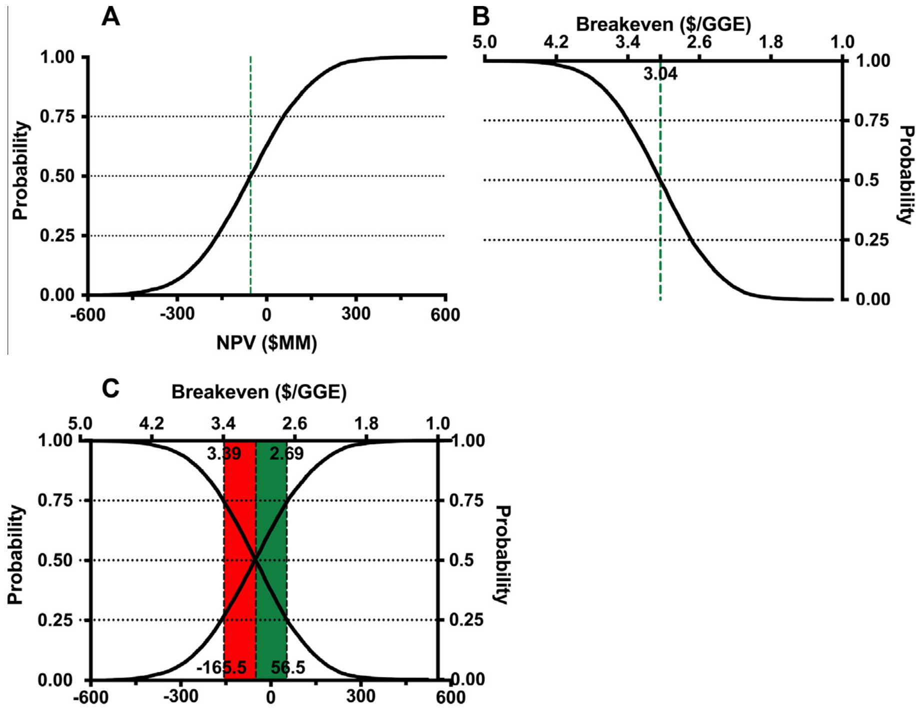

Fig. 4. Cumulative density distribution of NPV and breakeven initial price, based on all the uncertain variables. (A) The NPV Cumulative density distribution; (B) the breakeven initial price cumulative density distribution. (C) The overlap of figure (A and B). The shaded area in figure (C) represents 25th to 75th percentile area.

resulting breakeven price distributions can be fit to the closest standard distribution using common statistic methods. The @Risk software can perform this distribution fitting. The breakeven price at each percentile can be obtained.

The 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. Thus, in the case that mathematical deductions become too complicated to derive breakeven price from NPV, the programming method would be 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 by applying simulation data. Fig. 5A presents the standard deviation scaled regression coefficients. They are obtained by first regressing breakeven fuel price on key uncertain variables including capital investment, fuel yield, hydrogen price and feedstock cost, assuming constant future fuel prices, and then scale the coefficients by their standard deviations. It indicates how the standard deviation of breakeven price changes as one standard deviation increase in an uncertain variable. The number of observations equals the total number of iterations in simulations. Fig. 5B 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

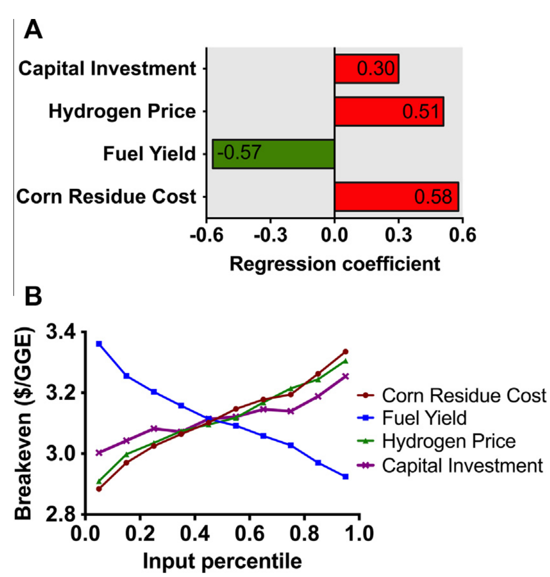

Fig. 5. Sensitivity analysis of breakeven price. (A) The regression coefficient of breakeven price on uncertain variables; (B) breakeven price sensitivity on input percentile of uncertain variables.

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). This study 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 mathematical method and a programming method were developed to quantify breakeven price distribution in a way that can consider future price trend and uncertainty. It demonstrated that the breakeven price distributions derived using methods developed were coherent with the corresponding NPV distributions regarding the percentile value and the probability of gain/loss. The statistic sensitivity analysis by applying simulation data also provided useful implications. The stochastic TEA and the methods of creating breakeven price distribution can be applied to evaluating other technologies.

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 [20]. 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. Reverse auctions are one policy option being considered for government procurement of advanced biofuels. 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 [13]. The study could have been considerably simplified if breakeven price distributions were applied. Furthermore, the scope of breakeven distribution can be broaden to any uncertain factors for the purpose of analysis, such as deriving a breakeven carbon tax distribution in a carbon mitigation policy analysis and breakeven land use change emission distribution in a life-cycle analysis.

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.

Acknowledgements

This work was partially funded by the US Federal Aviation Administration (FAA) Office of Environment and Energy as a part of ASCENT Project 001 under FAA Award Number 13-C-AJFE-PU. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the FAA or other ASCENT Sponsors.

Appendix A

See Table A.1.

Table A.1
Technical and economic assumptions.

Pathway	Fast Pyrolysis Hydroprocessing
Cost Basis	2011
Feedstock	Corn stover
Operating Hours/Year	7900
Project Life	22 years
Construction Time	2 years
Capital Cost % Spent in Land	1.3%
Capital Cost % Spent in Year 1	8%
Capital Cost % Spent in Year 2	60%
Capital Cost % Spent in Year 3	32%
Startup Period	0.5 years
Startup Production Rate	50%
Startup Variable Expense	75%
Startup Fixed Expense	100%
Feedstock Use (Mg/day)	2000
H_2 Use (tons/day)	48.6
Fixed Operating Cost ($MM)	14.23
Other Variable Cost ($MM)	1.75
Blending Rate (Gasoline % wt. of fuel)	50%
Electricity Generation (MW)	39.72
Electricity Usage (MW)	11.49
Electricity Price ($/kW h)	0.057
Inflation Rate	2.5%
Real Discount Rate	10%
Equity Fraction	50%
Loan Term	10-Year
Interest Rate[a]	7.5%
Income Tax Rate[b]	16.9%
Depreciation Term	7-Year
Depreciation Method[c,d]	Double declining balance
Working Capital Factor of Operation	40%
Sources	[1,13,20]

[a] Mean values are presented for the costs and productions that have uncertain variable involved.
[b] Interest is capitalized during construction.
[c] Tax benefits or losses are applied in the year they occur.
[d] Loan interest and depreciation are deducted from taxes.

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