Analysis and critical review of Monte Carlo simulation and decision analysis in EPA's 2014 RFS proposed rule

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by

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Executive Summary

A critical review of EPA's 2014 RFS proposed rule revealed the following:

1. In its Proposed Rule for the 2014 Standards for the Renewable Fuel Standards (RFS) Program, EPA describes a methodology for developing the proposed standards. The methodology involves developing ranges and probability distributions for renewable fuel production and using the probability distributions as inputs to a Monte Carlo simulation (MCS) model that aggregates the information into a single output distribution of the possible outcomes. In general, the modeling process was performed in a manner that was technically correct. The results of the analysis have been replicated for cellulosic biofuel, total renewable fuel, and advanced biofuel, using information in the proposed rule, along with information from the memorandum by D. Korotney in the EPA docket..
2. The only general issue with the modeling relates to the way probability distributions were assigned to the various companies/facilities expected to produce cellulosic biofuel in 2014. There are two major problems. First, is that the probability that a particular facility would produce no fuel was not directly specified. The approach of assigning a lower bound (5^{th} percentile) of zero implies that the probability of producing no fuel is the same (5%) across all facilities with the zero lower bound. This is an important modeling mistake. Especially for new facilities that were not yet producing, the probability of producing no fuel in 2014 should have been separately assessed.

   Second, the probability distributions assigned appear to ignore recent experience with cellulosic producers. In particular, the smooth six-month ramp-up period from start-up to a stable volume appears to be inconsistent with information from the two facilities that began producing in 2013, both of which appear to have experienced wide variation in production levels from month to month. Moreover, neither appears to have exceeded 10% of its capacity utilization in its first year.

   The MCS output distribution for total cellulosic fuel produced can be sensitive to the input probability distributions assigned. The proposed rule indicates 5^{th} and 95^{th} percentiles of 8 and 30 million gallons, respectively. However, applying more realistic probability distributions for Abengoa, DuPont, and Poet – probability of producing no fuel set to 20% for Abengoa and 40% for both DuPont and Poet; and if fuel is produced, a distribution with the 95^{th} percentile set at 20% of the plant's nameplate capacity, prorated over months the plant is expected to be open – results in 5^{th} and 95^{th} percentiles of 4.6 and 15.4 million gallons, respectively.

In order to improve the input probability distributions for new cellulosic facilities, EPA would benefit greatly by engaging the services of professional business analysts and experts that specialize in new-technology start-ups, especially in the renewable fuel industry. In addition, for these experts the EPA may benefit by using a more formal probability elicitation procedure.

3. A specific issue in the total renewable fuel model is that the amount of ethanol used in E10 is taken to be a fixed value, based on EIA’s forecast. Incorporating uncertainty into this forecast could have an impact on the output distribution.
4. The analysis appears to have been done in a straightforward, “no frills” manner. The proposed rule says nothing about whether or what kind of sensitivity analysis might have been performed. Sensitivity analysis is typically a key part of any analysis and can reveal important insights about the model. In this case, sensitivity analysis identifies Abengoa as the key driver in the cellulosic biofuel model, and biomass-based diesel as the key driver in both total renewable fuels and advanced biofuel. The extent of the potential impact of small changes in the distributions for these variables is demonstrated.
5. Given an output distribution from the MCS process, EPA requested comment on what value to choose as the standard (mean, median, mode, or another percentile.) The choice of a particular value to use as a standard should be recognized as a decision, and a “neutral methodology” would require proper cost-benefit analysis for all affected parties. Whether to use the mean, median, mode, or some other value boils down to this: EPA should do the economic analysis that would lead to a specific optimum value that can, in turn, be justified by the analysis. The agency appears to have the ability, and should be provided with adequate budgetary support, to perform such analysis as part of the proposed rule. The selected value would then be more than an arbitrary point chosen from the distribution but would be defensible on economic grounds.

Disclaimer

The American Petroleum Institute (API) engaged Professor Robert Clemen to perform an independent analysis of EPA’s proposed rule for the 2014 Renewable Fuel Standards. Professor

Clemen conducted this analysis and prepared this report with reasonable care and skill, utilizing methods consistent with best industry practice. No other representations or warranties, expressed or implied, are made by Professor Clemen. All results and observations are based on information available at the time of this report. To the extent that additional information becomes available or the factors upon which the analysis is based change, the analytical results and opinions expressed could be substantially affected.

1. Introduction

In its Proposed Rule for the 2014 Standards for the Renewable Fuel Standards (RFS) Program, EPA describes a methodology for developing the proposed standards. The methodology involves identifying input variables relating to the supply and demand of renewable fuels and developing ranges and probability distributions for those variables. The individual probability distributions are used as inputs to a Monte Carlo simulation (MCS) model that aggregates the information into a single output distribution of the possible outcomes.

For example, in developing the standard for cellulosic biofuel, EPA identifies a number of potential producers of cellulosic biofuels. Because the technology for cellulosic biofuel is still developing, the quantity of fuel from each producer's facility is highly uncertain. Taking each facility one at a time, EPA uses information about that producer and facility to develop a range of possible quantities of fuel generated. The range is used to specify the 5^{th} and 95^{th} percentiles of a probability distribution with a shape that matches the producer and facility's circumstances.

Ultimately, the question is how much total cellulosic biofuel will be produced in aggregate. If we knew exactly how much fuel would come from each producer, we would simply add up the quantities. MCS provides a way to do this in a probabilistic setting, and the basic concept is straightforward: Step 1, generate a random amount of fuel from each on the input distributions. Step 2, add those amounts to get the total amount. Now repeat steps 1 and 2 many times (typically thousands). Each iteration is called a "trial," and each trial gives a different total amount. Keep track of the total amount from each of the trials, and at the end they can be assembled into an output probability distribution for the total amount of cellulosic fuel produced. EPA can then consider aspects of that distribution, such as the mean, median, and percentiles, to understand what totals may reasonably be expected to occur, and use that information in choosing a standard, in this case a required volume of cellulosic biofuel.

MCS is typically used as part of a risk or decision analysis. The example above highlights the three key steps in the MCS process:

1. First is the modeling stage. The calculation model is created, with both input and output variables identified. As deemed appropriate, probability distributions are assigned to the input variables.
2. Second is the analysis phase, in which the MCS procedure is run. In practice, though, because the inputs and the calculation model include many judgments on the part of the modeler, the analysis involves multiple runs, trying different distributions, parameters, and scenarios in order to understand how sensitive the results are to the various inputs. If the results are highly sensitive to a particular input or some aspect of the model, then that part of the model would be revisited and, if necessary, refined to ensure the model's fidelity.
3. Third is the interpretation stage, in which results of the analysis are considered and incorporated as needed into the larger risk or decision analysis. In the case of the proposed rule, the decision is what specific number to use as the standard.

In this report, I will begin with an overall assessment of the MCS methodology as used to support the proposed rule, focusing on how each of the three steps above was executed. That will be followed by comments on the three specific applications of the methodology (cellulosic biofuel, total renewable fuel, and advanced biofuel).

2. Overall Assessment

First, the MCS modeling and analysis reported in the proposed rule is "technically correct" in my opinion. That is, using information in the proposed rule, along with some details from the memorandum by David Korotney (see footnote 81 in the proposed rule), I was able to replicate the results. That is good news; it means that the methodology described in the proposed rule accurately reflects the work that was done. However, we still need to evaluate the steps in the overall process.

2.1. Modeling

Modeling is the essence of analytical work. Many judgments are used to develop a calculation model that accurately reflects the system in question and, in this case, to specify ranges and probability distributions for the input variables. Modeling is sometimes said to involve as much art as science, and to a large extent, this is true; two analysts may create very different models of a system, depending on what each one deems to be the essential aspects of the system, and experts may have different information that can lead them to specify very different probability distributions for the same variable. Ultimately, though, the question is whether the model is appropriate for the purpose at hand. A very elaborate and complex hydrological model may be necessary to understand a specific hydrologic system in detail. However, if the problem is to manage an entire watershed, then a less elaborate model that provides an overview of the watershed and focuses attention on the management issue at hand may be more useful.

In the case of the proposed rule, the calculation model is straightforward; it is a matter of adding up quantities of fuel from different sources. Only addition is used. Everyone would agree on that, and so there is no question about the appropriateness of the calculation model.

More problematic is the selection of variables (sources of fuel) and the specification of probability distributions for them. The selection of variables appears to be reasonable. In each section of the report, EPA carefully enumerates possible sources and explains why each one should or should not be incorporated into the model. For example, in the cellulosic biofuel section, certain potential producers are excluded because EPA judges it highly unlikely that they will be able to start production during 2014.

After identifying variables, EPA examines the available information about each source of fuel in the model and specifies upper and lower bounds, thereby establishing a range for the amount of fuel from each source. The range is interpreted as a 90% confidence interval. That is, EPA judges a 5% chance (1 in 20) that the amount will fall below the lower bound and similarly a 5% chance that the amount will fall above the upper bound. The upper and lower bounds are thus used to specify the 5th and 95th percentiles of a probability distribution for the corresponding variable.

It is fairly common practice to identify upper and lower bounds as the EPA has done. The general reasoning behind the bounds are given in detail in the proposed rule. Understanding and documenting the reasoning used is an important aspect of the process, and EPA has done so.

There are a number of possible biases in probability judgment that have been well documented by psychologists. The two that are the most problematic in this case are overconfidence and optimism. Overconfidence in assessed ranges, like those that EPA proposes, means that the ranges would be too narrow relative to the probabilities specified. Upper bounds tend to be too low, and lower bounds tend to be too high. For example, when examining all of the times an individual has assessed a 90% confidence interval, one would expect 90% of the actual values to fall inside the corresponding assessed interval. In both experiments and realistic settings, psychologists have shown that the rate is on the order of 40%-60% falling inside the so-called 90% interval. When eliciting probability ranges from an expert, an analyst will work to counteract overconfidence by getting the expert to envision extreme possibilities, thereby extending the interval range.

Is overconfidence an issue in this case? Considering the upper bounds, it appears that EPA, in examining the information available, especially for new biofuel production facilities, has considered some “extreme” possibilities on the positive side. The lower bound is a different story. EPA has specified lower bounds of 0 for several of the cellulosic biofuel producers, but has not changed the percentile. With zero as the 5th percentile, they are essentially saying that there is a 5% chance that the facility will not open. Based on my reading of their reasoning in these cases, it would be very easy to argue that the probability of not opening could vary considerably across the facilities considered. For example, the DuPont plant in Nevada, Iowa, is projected by the company to begin production in the second half of 2014, and EPA has taken as a best-case scenario that production will begin in October. However, considering the experience of other facilities (notably INEOS Bio and KiOR, both of which began producing in 2013), delays are very likely. If the best case is that production begins in October, it would seem reasonable to assign a probability much greater than 5% that the plant will not begin production in 2014.

The second bias is optimism, a natural effect when considering new technology. It is easy to get caught up in the enthusiasm and possibilities associated with future developments, and it is arguable that optimism may, to some extent, account for the overambitious standards set in the original and subsequent RFS rules. Reading only what is included in the proposed rule, it might appear that EPA has managed to avoid being overoptimistic. If anything, the bounds specified appear to be on the conservative side; arguments could have been made for higher numbers. For example, in considering cellulosic ethanol producer Poet, EPA projects an upper bound of 6 million gallons, in contrast to Poet’s own projection of 7-12 million gallons. Similarly, EPA gives a lower bound of 0, reasoning that delays are common in completing and commissioning a commercial-scale cellulosic facility.

However, I will argue that EPA has indeed been overoptimistic in the ranges (and subsequent probability distributions) that it has assigned in the proposed rule. In particular, the assumption of a smooth six-month ramp-up period from zero to full production is unrealistic. Consider the experience of KiOR. In a December 23, 2013 press release, KiOR estimated that the total first-year (2013) production from its Columbus facility would be approximately 920,000 gallons, or just over 8% of the plant's nameplate capacity. Although we do not have up-to-date information from INEOS Bio regarding its Vero Beach plant, judging from RIN data taken from EPA's EMTS system, INEOS Bio cannot have produced at a higher rate than KiOR, and probably substantially less. Moreover, the RIN data, coupled with information in the proposed rule, seem to indicate that both companies experienced wide variation in production levels from month to month, circumstances not surprising given the fact that both companies are developing entirely new technologies. Taking a 10% utilization rate during the first year as a base case, then 20% would seem like a suitable "best-case" first-year utilization rate for Abengoa, DuPont, and Poet, pro-rated by the number of months out of the year that they are likely to be open. Such an approach should result in more realistic ranges and hence more appropriate probability distributions.

Having specified upper and lower bounds, the next modeling step is to assign probability distributions. As shown in Figure II.C-1 in the proposed rule, EPA chose to use only three types of distributions, normal (the classic bell-shaped curve), half-normal (the upper half of the bell-shaped curve), and skewed (a specific member from the so-called Weibull family). There are many different distribution types to choose from, and there is also the possibility of creating custom probability distributions – my MCS add-in for Excel permits me to do so quite easily. Is the choice of a particular distribution type crucial? Generally, no, especially in a case like this one, where the focus is on values that fall in the middle of the output distribution. (In some cases, for example when extreme events can lead to disastrous results, careful modeling of the tails of the input distributions can be important.) The three distributions used in the proposed rule are appropriate for the models and provide adequate flexibility.

As indicated above, the main caveats regarding the probability model relate to the cellulosic producers that have not yet begun production. First, basing the upper range on a smooth, six-month ramp-up process leads to unrealistic upper bounds and hence probability distributions with 95th percentiles that are too high. Second, in these cases zero is always the 5th percentile. In the calculation model, what this implies is that, if the random draw from an input distribution turns out to be less than zero, then it is set to zero. Thus, the probability of the facility producing no fuel, P(Vol=0), is always 5%, regardless of the situation. Thus, the fact that all facilities with a lower bound of zero have P(Vol=0) = 5% appears to be an artifact of the way ranges and probability distributions were assigned, rather than arising from careful judgment based on relevant information for each facility. In my opinion, this is an important modeling mistake. Especially for new facilities that were not yet producing, the probability of producing no fuel in 2014 should have been separately assessed. Including this probability in the MCS model is not complicated or difficult. For example, information in the proposed rule indicates that the DuPont and Poet plants are not expected to begin production until sometime in the second half of 2014. In both cases, technical difficulties could easily result in production being delayed until 2015. With this in mind, setting P(Vol=0) in the range of 30% - 50% seems plausible. As we will see below in considering the proposed cellulosic standard, the results can be quite sensitive to such changes.

One last point about the probability model is that there is no mention of the possibility that the input variables might have been correlated. Ignoring correlations is all too common in MCS analyses, and doing so can in some cases lead to substantial misrepresentation of the output uncertainty. Consider the cellulosic biofuel analysis. Although all of the businesses considered face considerable idiosyncratic risks, they all would be subject to general economic or policy conditions. For example, weak economic conditions could make investment dollars scarce for all companies. Not extending the renewable fuels tax credit could have a similar effect. How strong would the correlation be? Not particularly strong, given the large individual risks the companies face. However, a modest correlation coefficient of 0.2 is not out of the question. (While it is surprising that correlation was not mentioned, the good news, as we shall see below, is that none of the results are highly sensitive to correlation.)

It is worth mentioning here that there are established protocols for performing formal probability elicitations, and such protocols have been used many times in both public and private settings. EPA itself has used such formal procedures, notably in 2006 when eliciting expert opinion regarding the effects of PM 2.5. A National Research Council report (NRC 2002) provided guidelines for how EPA can incorporate uncertainty into its assessments. A complete, formal expert elicitation involves careful identification and selection of multiple experts; training the experts in the probability assessment process, including familiarizing them with psychological biases in probability judgment; structured 1-on-1 interviews to elicit probabilities and documenting the reasoning behind the probability judgments; and feedback to the experts to be sure they understand and confirm their responses. Such a process can be both expensive and timeconsuming and is not always feasible, nor is it always necessary. Many projects involve less formal procedures.

For the proposed rule, EPA has chosen to use a more informal process. In my opinion, this is appropriate. EPA staff should be knowledgeable about renewable fuels and have thorough access to relevant information. The proposed rule does an excellent job of reviewing the information and the reasoning behind the judgments made. Because the concern is primarily with the central portion of the output probability distribution, there is less need for careful specification of the input probability distributions. Given these circumstances, the time and expense associated with a full, formal expert elicitation was not called for. It may be beneficial to have an analyst review the probability judgments and work with those making the judgments to ensure that biases were minimized. In addition, EPA would benefit greatly by engaging the services of professional business analysts that specialize in new-technology start-ups. Doing so may have led to more careful assessments of P(Vol=0) when the lower bound was set to zero.

2.2. Analysis

As mentioned at the beginning, analysis involves more than just running the MCS procedure. In the same way that a good statistician will look at data from multiple perspectives to determine all that it has to say, a good risk or decision analyst will analyze the model in a variety of ways to develop as much insight as possible. In this case, we cannot say exactly what was or was not done; we can only see what is reported in the proposed rule. However, there are a few important insights that analysis can provide that are not mentioned. Most of these relate to sensitivity analysis of one sort or another. It is surprising, for example, that the proposed rule does not mention that the uncertainty in biomass-based diesel is the key driver in the models used for total renewable fuel and advanced biofuel. Similarly, Abengoa accounts for most of the uncertainty in cellulosic biofuel. Here is a non-exhaustive list of questions that might be answered by sensitivity analysis in this case:

- What are the key drivers of the uncertainty in each model?
- Which input distributions can be changed without affecting the outputs in any material way?
- How sensitive are the results to correlation in the variables?
- How sensitive are the results to P(Vol=0)?

- Do the specific shapes of the distributions matter?
- How do the results change if the 95th percentile is decreased? Increased?
- What if the upper and lower bounds are used to represent the 10th and 90th percentiles (a relatively common practice), instead of the 5th and 95th?

We will look at some of these possibilities when we consider each specific model below.

2.3. Interpretation and Decision Making

The decision that the EPA must make is to choose specific standards (values) for cellulosic biofuel, total renewable fuel, and advanced biofuel. The use of MCS is meant to support that in a way that allows them to incorporate their uncertainty about the various fuel sources. This is a laudable approach. The question, though, is how to use the output distribution. EPA itself seems somewhat at a loss in this respect. For each standard, the proposed rule reports the mean, median (50th percentile), mode (most "likely" value, or highest point on the curve), and the 25th and 75th percentiles. EPA proposes using the mean as the standard but requests comment on the merits of using other values.

In an interesting twist, if EPA does decide to use the mean of the output distribution, then the Monte Carlo procedure itself is not necessary. Because the calculation model involves only adding up several uncertain values, all that is required to obtain the aggregate mean is to calculate the mean of each input variable and then add up those means. The mean of the normal distribution is simply the midpoint between the assessed 5th and 95th percentiles. Calculating the mean of the skewed distribution is only slightly more difficult; the formula involves the distribution's shape and scale parameters. Calculating the mean of the half-normal distribution is similarly straightforward. The only complication would be to account for setting any negative values to zero. Doing so results in a probability mass at zero and will require modifying the standard formula for the mean of the half-normal.

Before addressing the deeper economic issues, we can consider the relative merits of the mean, median, and mode as candidate values to use as the RFS standard. The mean is a probability-weighted average of all possible values, and thus can be thought of as the most "representative" value. The median is the value that splits the range evenly in a probabilistic sense; the random value is just as likely to fall above the median as below. The mode is the most likely value; in this case, it is the high point on the output distribution. Arguments can be made in favor of all three, and each one is a reasonable choice. Personally, I prefer to use the median; I find the "just as likely to be above as below" characteristic to be compelling. In addition, the median is not affected by outliers, as is the mean. Also, the median does account for the probability distribution in a straightforward way, whereas the mode could turn out to be anywhere in the range. For the half-normal, for example, the mode is at one extreme of the range, making it questionable as a choice for a forecast. The median also represents something of a compromise; unless it coincides with the mean or mode (or both), it falls between the other two.

The language in the proposed rule suggests that the EPA is indeed looking at the standard-setting problem as a forecasting problem. As discussed in section II.D of the proposed rule, EPA is required to use a "neutral methodology" to generate a prediction of "what will actually happen." Taking that language at face value, it does sound as if the problem is to choose a single value to use as the forecast of the quantity of renewable fuel under consideration. If taken as a forecast, then the mean, median, and mode are all reasonable candidates. Although I prefer the median, the mean and the mode are just as reasonable. Moreover, for all three categories of renewable fuel, the mean, median, and mode are all relatively close.

However, I propose to re-frame the problem. The output distributions from the MCS process can be viewed as satisfactory probabilistic forecasts. When based on a carefully constructed model, expert probability assessments, and complete analysis, one could say that such probabilistic forecasts are indeed the results of a neutral methodology. These distributions represent the distillation of all available information into a reasonable probabilistic representation of the possible outcomes that may occur.

But if the output probability distribution represents the forecast, what does the selection of a particular value as a standard represent? I am sure that the EPA, as well as all of the obligated parties, understand clearly that choosing a standard is a policy decision with real economic consequences. And that begs the question, what is a "neutral methodology" for choosing a particular value? Decision analysts, management scientists, and operations researchers all would recognize this problem; it is similar to any organization's inventory problem. If the company orders too many of a particular item, it has leftovers that it may have to sell or discard at a loss. If it orders too few, it misses out on potential sales. The problem essentially boils down to balancing the costs and benefits on each side. In setting renewable fuel standards, there are likewise costs and benefits associated with each possible value that might be chosen. A careful economic analysis would quantify the costs and benefits for all affected parties, incorporating non-monetary costs and benefits as well, in order to find the value that optimizes the balance. This is no easy task. However, such cost-benefit analyses are done all the time by many governmental agencies. Even the EPA does these; when done in support of air pollution regulation, they are called Regulatory Impact Analyses. EPA's Technology Transfer Network has resources available online to support economic analyses of this nature.

Ultimately, my comment on whether to use the mean, median, mode, or some other value boils down to this: EPA should do the economic analysis that would lead to a specific optimum value that can, in turn, be justified by the analysis. The agency appears to have the ability, and should be provided with adequate budgetary support, to perform such analysis as part of the proposed rule. The selected value would then be more than an arbitrary point chosen from the distribution but would be defensible on economic grounds that would, in principle at least, make sense to everyone.

3. Detailed Comments on the Three Models

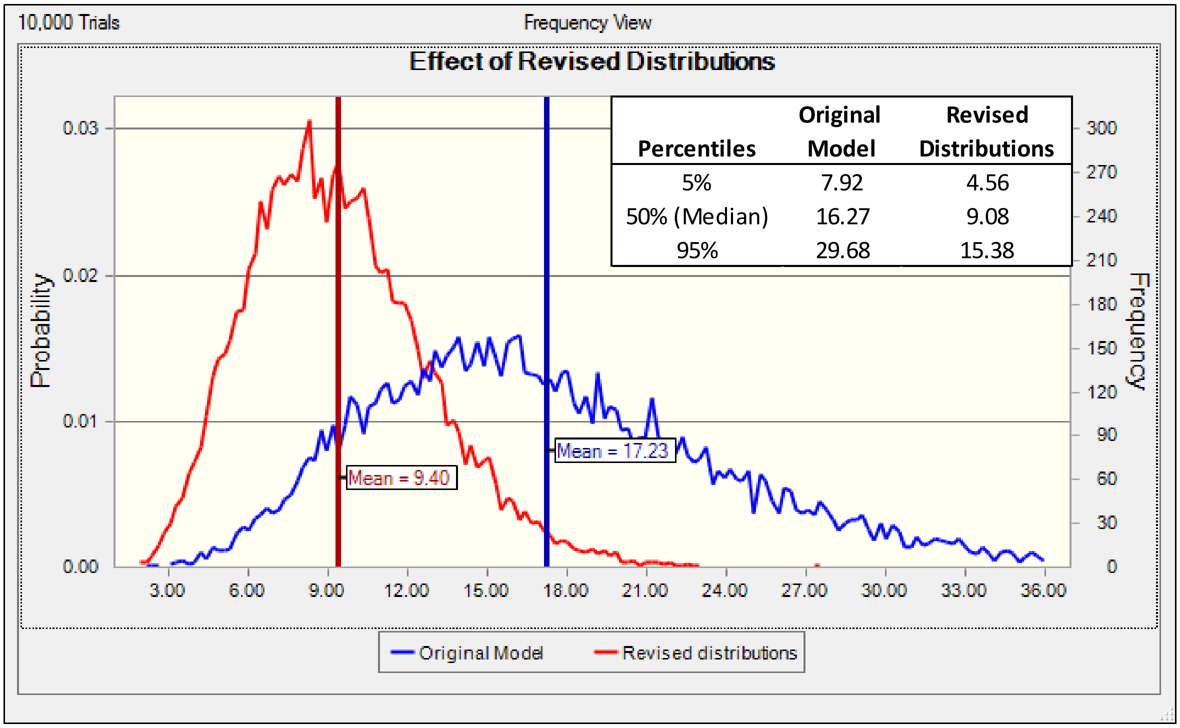
3.1. Cellulosic Biofuel

The cellulosic biofuel model suffers the most from the problem that P(Vol=0) was not carefully specified for the individual producers. As it stands, five producers with approved pathways were considered. Of these, Abengoa, DuPont, KiOR, and Poet all have 5th percentiles equal to zero, which, given the way the model was implemented, implies that P(Vol=0) = 5% for each of these producers. In contrast, CoolPlanet, Fiberight, LanzaTech, and Sweetwater were considered and excluded from the model on the grounds that none are considered in a position to produce any cellulosic biofuel in 2014. INEOS Bio was assigned a skewed distribution, and the minimum volume that distribution can generate is 1.71 million gallons, implying P(Vol=0) = 0%. So we have a situation where one producer is deemed certain to produce at least 1.71 million gallons, four are judged to have a 5% chance of producing nothing, and four are judged to have a 100% chance of producing nothing. In my opinion, this is not a satisfactory way to model the uncertainty associated with new technology and start-up firms. Surely there are aspects of the various enterprises that would indicate a finer distinction in terms of the likelihood of producing no cellulosic biofuel at all.

If the modeling suffers from the P(Vol=0) problem, it is to a large extent reprieved by the fact that Abengoa accounts for fully 72% of the variance in the aggregate total. In a distant second place is KiOR at 17%. What this implies is that Abengoa is the firm to focus on in terms of refining the probability judgment. However, relatively modest changes in Abengoa's distribution can result in meaningful changes in the aggregate distribution. For example, in the original model, the median aggregate output is 16.27 million gallons. Dropping Abengoa's 95th percentile from 18 million gallons to 16 million, an 11% decrease, results in the median aggregate output dropping to 15.71 million gallons. If in addition we increase Abengoa's P(Vol=0) from 5% to 20%, the median drops further to 14.62 million gallons. These two small changes in Abengoa's distribution have resulted in the median aggregate output dropping by over 1.6 million gallons, a 10% change. Noticing this effect that Abengoa can have on the results suggests that additional care be given to assigning Abengoa's probability distribution.

But what if we replace the three distributions for Abengoa, DuPont, and Poet with more realistic distributions as suggested above? In an experiment, I set P(Vol=0) 0.20 for Abengoa, and 0.40 for DuPont and Poet. For the 95th percentile, I assumed that Abengoa would be producing for nine months, Poet for six, and DuPont for three. (The numbers for DuPont and Poet are consistent with the timing assumptions in the proposed rule. According to a November, 2013, OPIS report, Abengoa anticipates beginning production in April, 2014.) Finally, I assumed that the best case for each of these three would be producing at 20% of capacity during those months. For INEOS Bio and KiOR, one could argue for more conservative distributions. For the purposes of the experiment, though, I chose to retain the original distributions for these two.

The results of these changes are striking, as shown by the graph below. Where my version of the original model gives 5th, 50th, and 95th percentiles of 7.92, 16.27, and 29.68 million gallons, respectively, the revised model gives 4.56, 9.08, and 15.38. (The small differences between my original model results and those in the proposed rule reflect inherent random variation in MCS.) If the mean of the output distribution were chosen as the cellulosic standard, then the changes made imply dropping the standard from 17.23 to 9.40 million gallons, a reduction by almost 45%.



The results are clearly sensitive to reasonable changes in the ranges and probabilities assigned to the producers' output. Given this sensitivity, along with the past overoptimism in EPA's forecasts of cellulosic, EPA should consider consulting business analysts that specialize in new-technology start-ups, especially for renewable fuel. In addition, it may be useful to use a more formal probability elicitation procedure with these experts.

I mentioned above that it would not be unreasonable to assign a modest correlation to the five producers, on the grounds that all are subject to common economic and policy drivers. Fortunately, the results are not highly sensitive to small correlations. Assigning a correlation of 0.2 to each pair of variables resulted in the median in the original model dropping from 16.27 to 16.09 million gallons. This change is only slightly greater than what might be expected due only to the random variation inherent in MCS. The aggregate distribution also is slightly more spread out than the original model.

3.2. Total Renewable Fuel

The model for total renewable fuel is generally good, with some quirks. In this case, the distribution for non-ethanol cellulosic amounts to the same distribution that was assigned to KiOR in the cellulosic biofuel model (because KiOR is the only firm producing non-ethanol cellulosic). And as before, there is the question of whether P(Vol=0) =0.05 is appropriate for KiOR.

The key driver of the uncertainty in total renewable fuel turns out to be biomass-based diesel. In the original model, it accounts for a whopping 88% of the uncertainty in total renewable fuel. With that much impact, we expect that even small changes will have a noticeable effect on the results. In fact, reducing biomass-based diesel's 95th percentile from 2400 to 2352 (10% of the range between the 5th and 95th percentiles) results in a slightly narrower distribution for total renewable fuel and drops the median from 15,181 to 15,166 million gallons, a change of 15 million gallons.

Given that biomass-based diesel can have this kind of impact on the aggregate distribution, it is worthwhile looking at the information that was used to develop its range and distribution, as described in Section IV.B.2.b. The lower end of the range was anchored by the 2013 standard of 1.28 billion gallons, reasoning that it would be very unlikely that less than that amount would be produced in 2014. To establish the upper end, several kinds of information were considered, including production capacity and utilization rates, whether the biodiesel tax credit would be extended through 2014, production data from EPA's Moderated Transaction System (EMTS), price and quantity forecasts for feedstocks, and an estimate of the amount of biodiesel that could be economically produced in 2014. The sources are summarized in Table IV.B.2.b-1.

Ultimately, EPA settled on a range of 1.28-1.6 billion gallons. This range is consistent with EMTS production forecasts. The arguments for these numbers appear reasonable. A half-normal distribution was used in the model, reflecting the belief that smaller volumes are more likely than larger volumes. (Note that the range and distribution were assigned under the assumption that the biodiesel tax credit would not be extended through 2014.) Nevertheless, given the potential impact of biomass-based diesel on the aggregate results, it may be appropriate to enlist additional expertise to confirm or refine this distribution.

The real surprise in the total renewable fuel model is how "Ethanol that can be consumed" is represented. The discussion on which this distribution is based focuses entirely on E85, and it comes to a reasonable conclusion that the range for E85 would be 100-300 million gallons, which corresponds to a range of 67-200 million gallons of ethanol. This range is tacked on to 12,887 million gallons of ethanol used in E10, a number that is derived from EIA's Annual Energy Outlook (AEO) forecast of total gasoline consumption in 2014 (see footnote 62). According to the proposed rule, Section IV.B.1.d, this amount of gasoline consumption is assumed to be fixed.

It is surprising that EIA's forecast would be assumed to be perfectly accurate, especially in light of its AEO forecasts over the past several years. Using past AEO reports available at EIA's website, I estimated that the AEO forecasts for gasoline consumption in 2011-2013 have erred on the high side by 3.5% - 5.5%. Given the amount of total renewable fuel involved, almost 13 billion gallons, even a modest amount of uncertainty can affect the results. I ran the model incorporating uncertainty in EIA's forecast using a normal distribution with a mean of 12,887 million gallons and standard deviation 128.87 million gallons (1% of the mean). In the original model, the median for total renewable fuel was 15,181 million gallons. With the added uncertainty, the median increased to 15,192 million gallons. Setting EIA's forecast standard deviation to 258 million gallons (2% of the mean), the median for total renewable fuel increased to 15,204 million gallons. This is a small difference in percentage terms (about 0.15%), but amounts to a change of 23 million gallons in total renewable fuel. The mean and mode show similar changes.

The real story, though, is not how the median changes, although the median is perhaps most relevant for standard setting. The dramatic change is in the spread of the distribution for total renewable fuel. In the original model, the 5th and 95th percentiles of total renewable fuel were 14,995 and 15,514 million gallons, respectively. In the revised model using 258 million gallons as EIA's standard deviation, the 5th and 95th percentiles become 14,707 and 15,715 million gallons, an increase in the spread by about 500 million gallons.

As with the cellulosic biofuel model, I re-ran the total renewable fuel model incorporating a correlation of 0.2 between each pair of variables. Again, the correlation results in a slight drop in the median (about 3.4 million gallons) and a slight increase in the distribution's spread. As above, these are very modest changes, suggesting that careful modeling of correlations is not necessary.

3.3. Advanced Biofuel

Given the ground covered in reviewing cellulosic biofuel and total renewable fuel above, the story about the advanced biofuel model can be told rather quickly. This model includes the five cellulosic biofuel producers that were included in the cellulosic model. The problem of specifying P(Vol=0) would seem to apply here as well. In addition, the model includes biomass-based diesel, using the same distribution found in the total renewable fuel model. Domestic non-ethanol advanced biofuel is also included and appears to have been used in the total renewable fuel model with the same distribution, just without the "domestic" label. Thus, all of the variables and distributions in this model have been seen before.

The story here is easily told, because biomass-based diesel again accounts for the lion's share, over 94% this time, of the variation in the aggregate distribution. In this case, dropping the biomass-based diesel's 95th percentile from 2400 to 2352 million gallons (same as before), the median of the output distribution drops from 2172 to 2157 million gallons, a change of 15 million gallons. The fact that biomass-based diesel controls so much of the variation in the distribution for advanced biofuel reinforces the need to ensure that it's input distribution reflects all available information.

Incorporating a correlation of 0.2 into the model makes almost no difference in the output distributions. The median is virtually the same as in the original model, and the distributions are only slightly more spread out. Increasing the correlation to 0.5 changes the median a bit more (less than 1 million gallons) and again spreads the distributions. Given that biomass-based diesel controls so much of the variation by itself, it is perhaps not surprising that incorporating correlations among the variables has little impact.

About the Author

Robert Clemen is Professor Emeritus of Decision Sciences at Duke University's Fuqua School of Business. He has broad interests in the use of decision analysis for organizational decision making, and special interests in the psychology of judgment, assessing expert probabilities, the effectiveness of decision-making techniques, and using decision analysis to help organizations become environmentally sustainable. The author of the widely used text Making Hard Decisions, Professor Clemen has over thirty years of teaching experience, including courses on decision analysis and analytical tools for sustainability. He has published over fifty scholarly articles that have appeared in such journals as *Management Science*, *Operations Research*, *International Journal of Forecasting*, *Decision Analysis*, and others. Professor Clemen's consulting and executive teaching include work for corporations, utilities, and government agencies, and have covered such diverse areas as salmon farming, offshore oil leasing, avalanche prediction, nuclear waste storage, electric power demand forecasting, and environmental policy. He was a member of the National Research Council committee that produced Models in Environmental Regulatory Decision Making (Washington, DC: National Academies Press, 2007) and served on the Advisory Committee for the National Biodiesel Board Sustainability Task Force, 2008-2009. His CV is attached.

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PROFESSIONAL EXPERIENCE

- 2011-present. Professor Emeritus of Decision Sciences, Fuqua School of Business, Duke University
- 1995-2011. Associate and Full Professor of Decision Sciences, Fuqua School of Business, Duke University
- 1994-1997. Senior Scientist, Applied Decision Analysis, Inc., Menlo Park, CA
- 1993-1995. Senior Researcher, Decision Research, Eugene, OR
- 1989-1990. Visiting Associate Professor, Fuqua School of Business, Duke University
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AWARDS AND HONORS

RESEARCH AND PUBLICATION AWARDS

- Ramsey Medal, 2012. Lifetime achievement award by the Decision Analysis Society (INFORMS).
- Decision Analysis Publication Awards, Decision Analysis Society (INFORMS):
    - Fox, C. R., & Clemen, R. T. (2005). Subjective probability assessment in decision analysis: Partition dependence and bias toward the ignorance prior. *Management Science 51*, 1417-1432.
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- Forecasting Publication Award, International Institute of Forecasting:
    - R. T. (1989) Combining forecasts: A review and annotated bibliography. *International Journal of Forecasting 5*, 559-583.

TEACHING AWARDS

- Page Prize for Sustainability Curriculum, Honorable Mention, 2010
- Outstanding Professor, Fuqua Global Executive MBA, 2000
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- Outstanding Teacher Award, MBA Program, U. of Oregon, 1987

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Lantos, P., Brinkerhoff, R., Wormser, G., Clemen, R. (2013) Empiric antibiotic treatment of erythema migrans-like skin lesions as a function of geography: A clinical and cost effectiveness modeling study. *Vector-Borne and Zoonotic Diseases*, *13*, 877-883.

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COURSES TAUGHT

Decision Analysis (Undergraduate, MBA, PhD)

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Environmental Sustainability: Modeling and Analysis (MBA)

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SELECTED SERVICE ACTIVITIES

PROFESSIONAL ORGANIZATIONS AND ACTIVITIES

Chair, *Decision Analysis* Editor Search Committee, INFORMS. 2012.

Editorial Board member, *European Journal on Decision Processes.* 2012-present.

Fellow, Society of Decision Professionals. 2011-present.

National Biodiesel Board Sustainability Task Force, Advisory Committee member. 2008-2009.

Editorial Board Member, *Decision Analysis*, 2007-present.

National Academy of Sciences Committee on Model Use for Regulatory Decision Making, 2004-2007.

Founding Co-Editor, *Decision Analysis* (co-editor with Don Kleinmuntz), 2001-2006.

Member, Harvard Center for Risk Analysis Advisory Committee, Harvard University 1999-2001.

Associate Editor, *International Journal of Forecasting*, 1992-1996.

Departmental Editor (Decision Analysis), *Management Science*, 1992-1995.

SELECTED CONSULTING ENGAGEMENTS

2011-2012. Omaha Foreign Exchange Corporation. Decision and risk management.

2010. BC Hydro. Probability forecasting for customer response to demand-side management programs.

2009. Environmental Protection Agency. Multiattribute decision making for research proposal funding.

2007. Army Corps of Engineers. Reviewer for Louisiana Coastal Protection and Restoration project.

1999. Cadmus Group. Decision analysis support for USEPA procedures.

1998. EC/R Inc. Advisory role in EPA risk assessment project.

1997. Alceon Corporation. Mathematical statistics consultant for risk analysis project.

1995. Eli Lilly & Co. Provided a 2-day workshop on structuring decision models.

1992-1994. Southwest Research Institute, San Antonio, TX. Risk assessment regarding future climate change at Yucca Mountain, Nevada.