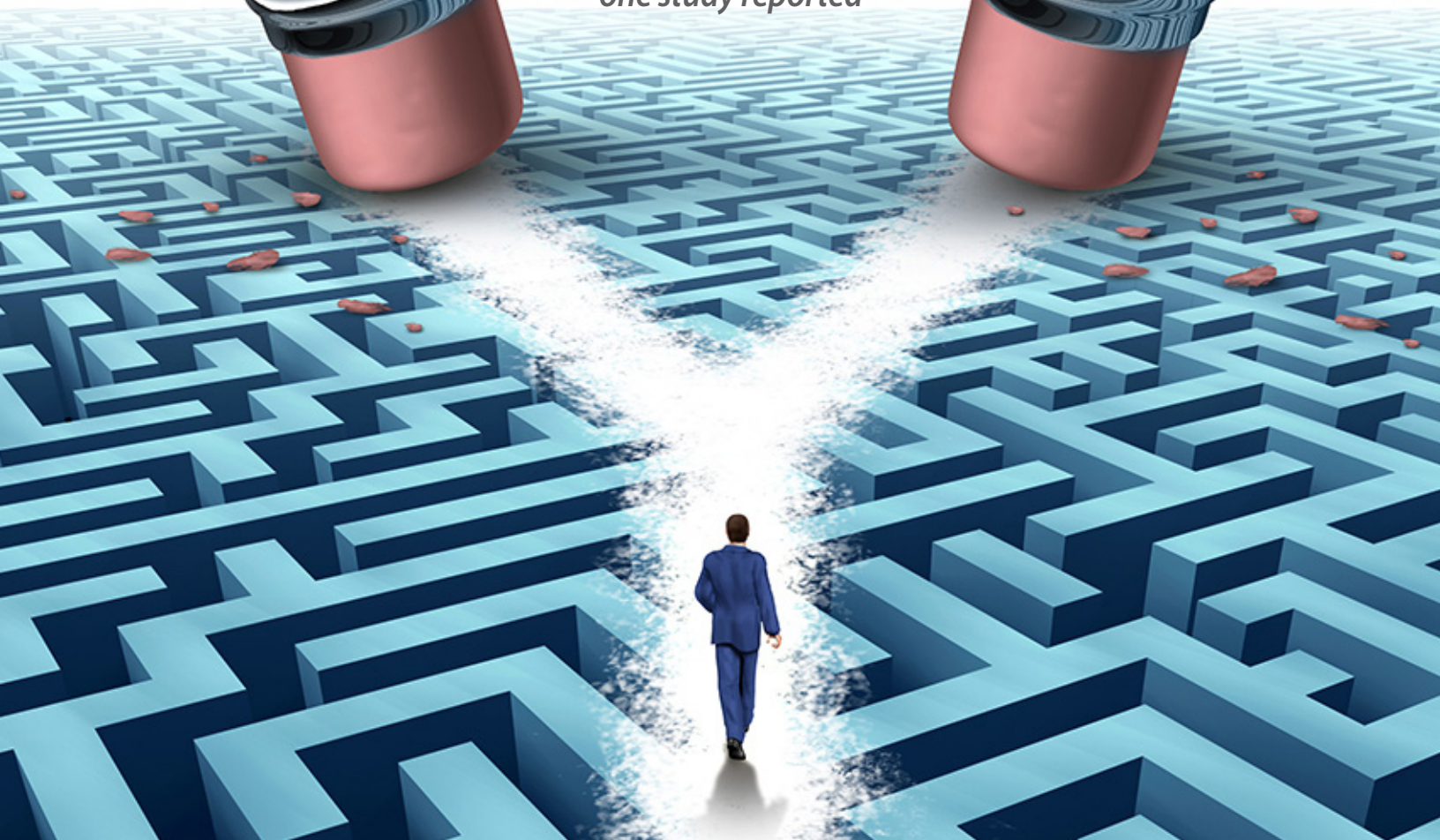


## Recent studies measure bias in production forecasts

*Proved reserves filed with the SEC were within 1 percent of actual reserves, one study reported*



**H**istorical oil and gas production has not measured up to production forecasts, say industry “scorekeepers.” They say that on average, companies filing with regulators have let bias creep into reserves estimates and production profiles. Compounding the situation is few companies look back at production records to compare them to forecasted numbers to recalibrate, according to these researchers.

For estimated future production to be reliable, operators have to follow a development plan and drilling schedule. An operator may veer from its plans for various “unforeseen” reasons, including poor drilling results, new well and other

technical information, mid-year budget revisions, increased costs, decreased commodity prices, transportation bottlenecks, new regulations, mechanical failure, divestitures, acquisitions, change in ownership and direction, change in drilling priorities, delays by service companies, delays for government approvals and even pandemics.

All that makes recalibration more difficult. In addition, bias does not necessarily play a role in 100 percent of extraneous factors that change company plans, execution and therefore, forecasts.

This article will summarize recent findings of two surveys

on the effect of bias in reserves and production forecasts.

One surprising conclusion was that proved reserves estimates filed with the SEC were within 1 percent of actual reserves, although this says nothing about outliers and ranges of reserves values. By definition, estimates of proved reserves have at least a 90-percent probability that the actual amount produced will equal or exceed the estimate.

Authors of the paper, “Technical Revisions Reveal Overconfidence in U.S. and Canadian Reserves Estimates,” SPE Paper No. 201116-PA, stated the following:

“Because U.S. companies are not required to distinguish between (1P and 2P) categories, their single estimates end up somewhere in between, and apparently, closer to the P50 value. The U.S. 1P estimates disclosed seemed to satisfy only the certainty criterion for 2P reserves,” the authors stated, while recognizing other possible causes.

The U.S. data set covered more than 10 years of information during 2007 to 2017 on 32 companies, raising questions as to what constitutes a representative sample size of public issuers in the U.S. market. The data set was limited because only companies, with revisions of previous estimates and revisions caused by price variations, fit the survey design.

“The U.S. analysis could be biased toward companies that provided this information,” stated the authors.

### SEC-case reserves reports

Several press reports this year have focused on questionable disclosures of reserves and production forecasts, especially in the Permian Basin, where infill or extension wells are robbing parent wells of pressure and production.

Weighing in on the topic, CEO **Dean Rietz**, said, “We strive to keep our clients compliant with SEC reporting rules while documenting full value of their assets as permitted. SEC-case proved reserves are considered conservative by many.”

Producers plan their business cases, including field development projects, on 2P (sum of proved and probable) reserves, not proved.

“We look for consecutive, upward, year-to-year reserves revisions in proved reserves since we know the SEC frowns on the opposite. We know we are doing a good job, if the forecasts are not far off from actual production and upward revisions are not significant,” said Rietz.

### Bias: Overconfidence and optimism

Quantifying bias in decision-making is not a recent trend. Researchers have measured bias in reserves disclosures for 44 years, beginning with **E.C. Capen**, who recognized tendencies for overconfidence and optimism and published his findings in the *Journal of Petroleum Technology*.

Before that, psychologists **Amos Tversky** and **Daniel Kahneman** introduced the notion of cognitive biases in 1972.

Biased thinking and decision-making are rooted in human nature. They arise in budget-justification processes. Incentives and bonuses for meeting reserves targets encourage bias. The causes for bias include motivators toward high-side forecasts, excessive pride of ownership, emotional carryovers, delusion and deception.

The upstream sector has distilled the reasons for bias to two measurable human tendencies — overconfidence and optimism.

### Overconfidence

Humans, including reserves evaluators, have a natural tendency for overconfidence, which is an underestimation of uncertainty. Evaluators gauge uncertainty levels in their production forecasts to reflect a range of possible outcomes from the P10 high to the P90 low.

The ability to do this objectively and generate reliable estimates is directly related to the overconfidence/underconfidence continuum.

An overconfident evaluator has a narrower range of possible outcomes, leaving little room for a missed call at early field development stages when data is insufficient.

### Optimism

Optimistic forecasts give greater weight to the upside. Evaluators can develop optimistic forecasts by reacting to motivators or by overlooking human error. Underestimating downside causes unpleasant surprises — more downtime than anticipated, longer-than-expected durations for drilling and completions and lower-than-expected actual oil production.

Pessimism, on the other hand, is responsible for undervaluing oil and gas assets. That bias handicaps a company in trying to take advantage of opportunities in acquisitions and divestitures and in portfolio management.

In the A&D world, sellers seldom undervalue assets. It is widely known that “seller’s reports” boost reserves volumes to the high side to entice buyers. Taken to an extreme, biased reports underpin “pump and dump” schemes.

### Bias in Charted Territory

Reserves engineers don’t have to take a Psychology 101 course to realize underlying human tendencies get in the way of objectivity. Certainly, the evaluation sector has attempted to reduce bias by increasing reliance on automated routines, machine learning, blind fitting and artificial intelligence, which has been an option in decline-curve analysis programs for 40 years. The problem with black boxes is bias-influenced, erroneous assumptions and notoriously

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bad data — garbage in, garbage out — can skew model results.

The chart, opposite, shows an estimated reserves distribution represented by the red curve. It is overconfident with a narrower estimated probability range than the true distribution (blue curve). Ideally, actual reserves fall within the P10/P90 range approximately 80 percent of the time.

The curve also has shifted to the right of the mean P50 value of the true distribution, indicating an optimistic forecast of reserves.

### Quantitative analysis

Through quantitative analyses, two Society of Petroleum Engineers technical papers, finalized this year, studied the effect of bias in production forecasts and reserves.

One of the papers, peer approved in February, outlines due diligence procedures for evaluators, investors and regulatory agencies.

The SPE paper, previously cited in this article, was written

**“...proved reserves estimates filed with the U.S. Securities and Exchange Commission were within 1 percent of actual reserves.” — Gomez et al.**

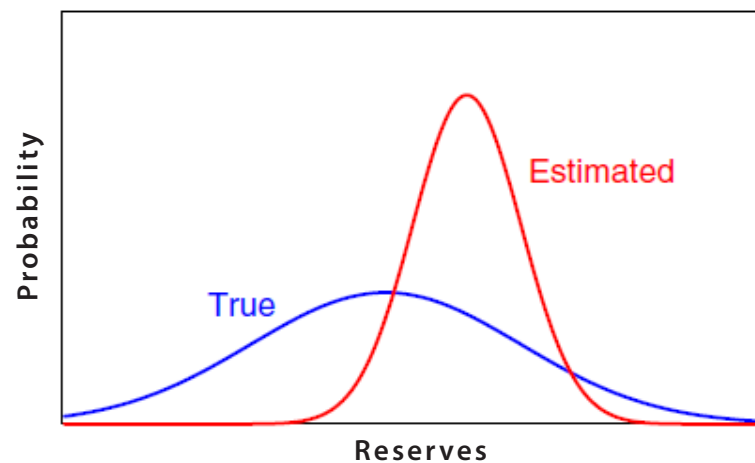
by first author **Diana Gomez** at Texas A&M University. Professor **John Lee** is also an author as well as **Duane McVay**, both at Texas A&M.

They analyzed bias in 1P or P90 reserves reported to the SEC and Canadian Securities Administrators (CSA) as well as 2P or P50 reserves also filed with the CSA. Public issuers in Canada report proved and probable reserves under National Instrument 51-101.

As previously stated, Gomez et al. tracked technical revisions (TRs) from reserves reconciliation reports during 2007 to 2017. They analyzed the reliability of a group of probabilistic assessments on calibration plots to compare the number of actual outcomes to the probabilities of outcomes.

Their tracking of TRs allowed for the review of changes attributable to “the skills and practices of the assessors” with no effect from economics, including price, a major change agent. The authors use the term ROTP (reserves other than price). A common industry term is “technical reserves.” However, that expression ignores that evaluators estimate reserves under economic limits.

The method presented by Gomez et al. may also prove to be valuable to the business and trade press and to financial analysts who follow public oil and gas companies in U.S. markets. While filers in Canada report TRs separately, filers in the U.S. market combine technical and economic revisions,



*Estimated reserves distribution that is overconfident and optimistic.*

making it difficult to isolate TRs.

To overcome this, Gomez et al. calculated ROTPs by subtracting price-related revisions from revisions of previous estimates. The difference is desired TRs are subject to some assumptions.

They stated, “TRs occur primarily because of new subsurface information acquired over the year.” As examples, they cited production data, new wells and test data.

Gomez et al. examined TRs by year, company and company size. For companies reporting to Canada authorities, the authors evaluated TRs by fluid type (light/medium oil, heavy oil and gas) and resource type (conventional vs. unconventional). They found several relationships between reliability and categories.

The other paper, “Production Forecasting: Optimistic and Overconfident – Over and Over Again,” (SPE Paper No. 195914-MS) was also peer approved in February. **Reidar B. Bratvold** at the University of Stavanger (UiS) is the first author. Also contributing were **Erlend Mohus** at the UiS and **David Petutschnig** and **Eric Bickel**, both at the University of Texas.

They analyzed private filings received by the **Norwegian Petroleum Directorate (NPD)**. Bratvold et al. reviewed initial annual oil production forecasts at the time of the financial investment decision through the fourth year. Several international oil companies have a sizable presence in Norway.

The authors started with company filings on 85 oil and gas fields. They eliminated 30 fields that did not produce oil, had poor or missing associated data, experienced startup delays and had associated data past 2017. Oil production was the only focus.

In their paper, the authors did not comment on any effects from reducing the sample size. In some cases, a select group of qualified fields may not represent the larger, uncultured population.

Bratvold et al. tracked technical revisions on the fields to



compare probabilistic estimated (P90/mean/P10) volumes to actual production. In total, they analyzed 549 forecast years from 55 oil fields in the Norwegian continental shelf.

The paper offers a method to reduce bias by encouraging and rewarding evaluators for providing unbiased forecasts. Bratvold et al. cited one method, reference-class forecasting, that provides an outside view of a given project by referencing past comparable projects. They plan to elaborate on that method in a subsequent paper.

Referring to his paper recently, Bratvold said, “We argued that there are two categories of biases: cognitive and motivational. We did not argue that one is more important than the other. However, we did suggest that motivational biases stemming from organizational structures and incentive systems may be significant.”

Several disciplines depend on forecasting and refining their models over time.

“Weather forecasting ... has experienced significant improvements over the last two decades: 7-day forecasts made today are as accurate as 5-day forecasts 22 years ago,” stated Bratvold et al. “Unfortunately, in the oil and gas industry, the development of probabilistic forecasting systems has not been accompanied by commensurate effort in developing procedures to assess the performance of ... forecasts.”

Differentiation between deterministic and stochastic methods is a distinction without a difference to Gomez et al. “Reserves estimates are probabilistic assessments regardless of whether the reserves are estimated deterministically or probabilistically,” they stated.

Bratvold et al. reviewed fields operated by companies under the NPD resource classification system. It requires companies to file petroleum volumes in low, base and high uncertainty categories.

Although base-case estimates are calculated using

deterministic or stochastic methods, all forecasts they used were probabilistic.

### Gomez scorecard

- Gomez et al. found that filers in Canada overestimated 1P reserves and underestimated 2P reserves. U.S. filers overestimated reserves more often than Canadian public issuers.
- Filers in U.S. markets reported positive revisions of 51 percent for 1P reserves, a significant departure from the 90-percent reasonable certainty level in definitions of proved reserves.

The irony: Proved reserves estimates were within 1 percent of actual reserves.

- U.S. filers were neutral to completely overconfident and moderately to completely optimistic.
- Overall, filers in Canada were moderately overconfident and slightly pessimistic.
- Canadian filers showed no improvements in overconfidence or pessimism in reserves reconciliations over 11 years. U.S. filers do not disclose the data necessary to track the two components of bias.

### Bratvold scorecard

- Bratvold et al. found an 84-percent chance that the actual production in the first four years will be less than the P50 (mean) forecast, and a 59-percent chance it will be less than the P10 forecast.
- Empirical data shows there is only a 31-percent chance that the actual production will fall within the P10-to-P90 range.
- The production shortfall relative to production forecasts is as poor now as it was 22 years ago.
- There were no signs of performance improvements, despite advances in uncertainty modeling, which suggests biased input is at work.

Both of these papers outlined assumptions and hypothesized likely reasons for bias. The authors defined the scope and design of the surveys, detailed their procedures, and presented instructive charts and graphs. Gomez et al. analyzed the relationship between bias and company size, product type, etc. The papers are available for purchase at [www.onepetro.org](http://www.onepetro.org).