FINAL MODELING RESULTS

Linear Programming Optimization Model

Questar Gas has utilized for a number of years, a computer-based linear-programming optimization (LPO) model to evaluate both supply-side and demand-side resources. This software product, marketed under the name of "SENDOUT," is maintained by Ventyx headquartered in Atlanta, Georgia. Ventyx is owned by ABB, a global power and automation technology group headquarted in Zurich, Switzerland with approximately 117,000 employees. SENDOUT is used by more than 100 energy companies for gas supply planning and portfolio optimization.

SENDOUT has the capability of performing Monte Carlo simulations thereby facilitating risk analysis. The Monte Carlo method utilizes repeated random sampling to generate probabilistic results. It is best applied where relative frequency distributions of key variables can be developed or where draws can be made from historic data. Because of the need for numerous random draws, this method has been facilitated by the availability of high-speed computer technology.

Questar Gas is using a new release of SENDOUT this year, Version 14.0.0. This version was installed during February of 2011. SENDOUT Version 14.0.0 utilizes more powerful database tools, Microsoft SQL Server or SQL Server Express. In previous versions, Microsoft Access was used. SENDOUT Version 14.0.0 also has the capability of defining logical pricing relationships (baskets) within the model.

In performing gas supply modeling, Questar Gas representatives work closely with consultants from Ventyx. The Ventyx consultants are very familiar with the gas supply modeling approach of the Company and they are comfortable with how the Company utilizes and configures the SENDOUT model.

Constraints and Linear Programming

While the concepts of linear programming date back to at least the early 19th century, it was not until the middle of the 20th century that this approach began to be more widely accepted as a method for achieving optimal solutions in practical applications. In summary, linear programming problems involve the optimization of a linear objective function subject to linear constraints. Constraints are necessary in the determination of a maximum or minimum solution. Constraints must be linear functions and can either represent equalities or inequalities. An example of an inequality constraint in the natural gas business would be that the quantity of natural gas that can be transported over a certain segment of an interstate pipeline must be "less than or equal to" a certain level previously contracted for with that pipeline company. Another example of an inequality constraint would be the production available from a group of wells providing cost-of-service natural gas. The levels of this resource that can be taken can never exceed the maximum level available as production naturally declines over time. All resources are defined by constraints including purchased gas. Some peaking contracts have minimum levels that must be taken during an agreed-upon period of time which would be translated into a “greater than or equal to” constraint. Constraints must be carefully defined to accurately reflect the problem being solved. The arbitrary removal of required constraints results in an inaccurate solution. For example, if the constraint on how quickly the Company’s capacity at the Clay Basin storage facility can be refilled were to be removed, the model would assume that it could be done instantaneously, resulting in an unrealistic solution. The removal of all constraints in a linear programming problem results in no solution being obtained. Questar Gas periodically reevaluates the constraints in its SENDOUT model to determine if they accurately reflect the realities of the problem being solved.

Monte Carlo Method

When performing Monte Carlo analysis, the length of computer run times can become an issue. To have a meaningful simulation, it is important to have a sufficient number of draws (typically hundreds). Each draw consists of one deterministic linear programming computer run. With the complexity of the Company’s modeling approach, one simulation usually takes several days to run. The base Monte Carlo simulation developed by the Company this year utilized 1,198 draws.

When the developers of SENDOUT incorporated the Monte Carlo methodology, they limited the number of variables for which stochastic analysis can be applied to avoid excessive computer run times. The two variables which they appropriately determined should be included are price and weather (within SENDOUT demand is modeled as a function of weather). No other variables have a more profound impact on the cost minimization problem being solved by SENDOUT than these two.

The output reports generated from the SENDOUT modeling results consist primarily of data and graphs. Most of the graphs are frequency distribution profiles from a Monte Carlo simulation. Many of the numerical-data reports show probability distributions for key variables in a simulation run. The heading “max” in these reports refers to the value of the draw in a simulation with the highest quantity. The heading “min” refers to the value of the draw in a simulation with the lowest quantity. The heading “med” refers to the median draw (or the draw in the middle of all draws). Questar Gas believes that the mean and median values are good indicators of likely occurrence, given the underlying assumptions in a simulation. Many exhibits in this report also include a base case number to show how the base case compares to the mean and median. The base case will be discussed in more detail later in this section. Also in these data reports are the headings “p95,” “p90,” “p10,” and “p5.” The label “p95” on an output report means, based on input assumptions, that a 95 percent confidence exists that the resulting variable will be less than or equal to that number. Likewise, a “p10” number suggests that there is a 10 percent likelihood that a variable will be less than or equal to that number. These statistics and/or the shape of a frequency curve help define the range and likelihood of potential outcomes.

Natural Gas Price

The price for which natural gas supplies can be purchased in the future is extremely difficult to model with any level of accuracy. It is not uncommon for the best industry forecasts to be off by more than a factor of two or less than a factor of 0.5. Most of the natural gas purchased by Questar Gas is tied contractually to one or more of ten area price indices. Three of those indices are published first-of-month prices for deliveries to the following interstate pipeline systems; KRGT, Questar Pipeline, and Northwest Pipeline. The remaining are published daily indices for KRGT (3), Questar Pipeline (2), Southern California Gas (1), Northwest Pipeline (1), and one basket combining KRGT, Northwest Pipeline and Questar Pipeline indices. To develop a future probability distribution, Questar Gas assembled historical data and determined the means and standard deviations associated with each price index. Questar Gas then utilized the average of two price forecasts developed by PIRA[1] (19 months) and CERA[2] (252 months) as the basis for projecting the stochastic modeling inputs. Forecasted standard deviations have been scaled up a pro rata based on prices to more accurately mirror reality. Exhibits 9.1 through 9.36 show, for the first model year, the resulting monthly price distribution curves for the first-of-month prices and the daily prices for each of the price indices used in the base simulation.

Weather and Demand

In addition to the price of natural gas, the other single most unpredictable variable in natural gas resource modeling is weather induced demand. Questar Gas makes available to the SENDOUT model 82 years of weather data. It should be noted that when forecasting future demands, heating degree days are stochastic with a mean and standard deviation by month. This number, along with usage-per-customer-per-degree-day and the number of customers, is used to calculate the customer demand profile used by the model. The stochastic nature of the heating-degree-days creates a normal plot for degree days based on the 1,198 draws. For each month of simulation, the model randomly selects a monthly-degree-day standard-deviation multiplier to create a draw-specific monthly-degree-day total. It then scans through 82 years of monthly data to find the closest matching month. Then the model allocates daily degree-day values according to the degree-days in this historic month pattern. Exhibits 9.37 through 9.49 show first the annual and then the monthly demand distribution curves for the first year of the base simulation. Exhibit 9.50 shows the annual heating-degree-day distribution.

In prior years, before Questar Gas utilized Monte Carlo modeling techniques, a high demand and a low demand scenario were modeled as part of a sensitivity analysis. Currently, with the use of a Monte Carlo modeling approach, the wide variability in weather-

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[1] PIRA Energy Group, Inc. (PIRA) is an international energy consulting firm with expertise in energy market analysis and intelligence. PIRA's client base exceeds 550 entities in over 60 countries.
[2] Cambridge Energy Research Associates, Inc. (CERA) is a leading advisor to international energy companies, governments, financial institution, and technology providers. CERA has a staff of 200 employees in nine offices worldwide.

induced demand resulting from historical weather data is broader than any reasonable range of load growth scenarios. This year there are 1,198 deterministic cases in the Monte Carlo simulation, each with a different demand level, thus obviating the need to model just one high and one low demand case.

Peak Day and Base Load Purchase Contracts

An important consideration in the modeling process is the need to have adequate resources sufficient to meet a design-peak day. The design-peak day for the 2011/2012 winter-heating season has been determined to be 1.28 million Dth per day at the city gates. The design-peak day for many years has been defined to be a 1-in-20-year weather occurrence. The most likely day for a design peak to occur is on January 2, although, the probability of a design peak occurring on any day between mid-December and mid-February is relatively flat. Even though it is unlikely that a design-peak day will occur this year, the Company must be prepared to meet such a need should it occur. Selecting a draw from a Monte Carlo simulation that utilizes on the maximum demand day a level of resources approximately equaling the design-peak day has proven to be problematic in that the SENDOUT model selects too much base-load purchased gas for a typical weather year. The draws which have a design-peak-day occurrence also tend to be much colder than normal throughout the entire year. The solution to this dilemma is to perform a statistical clustering analysis of all the Monte Carlo draws for first-year peak demand versus the median level of first-year annual demand.[3] The result of this clustering exercise is a scatter plot that shows groups of draws. These cluster points or groups represent draws that are most closely alike in terms of peak-day requirements and annual demand. A cluster point is then chosen that we believe will meet both a realistic annual demand and peak day.

A second SENDOUT scenario is then executed, with the unused RFP packages removed, and only those "cluster point" packages remaining. One of the purposes of this run is to verify that adequate purchased gas resources at the least cost will be available in the remote event that a design-peak day were to occur. The optimizing nature of the SENDOUT model helps to make this happen. This year, of the 1,198 draws generated in this process, 8 draws would exceed the design peak-day requirement of 1.28 MMDth. In other words, this scenario has enough resources to meet a peak-day event. Most of the base-load purchased-gas resources, with their associated time-availabilities, must be committed, during the springtime, prior to the beginning of the gas supply year, to be ready for cold weather in the fall. Patterns of usage for storage resources, spot gas, and cost-of-service gas do not need to be committed to before the gas year begins. This modeling approach also lends itself to performing operational analysis periodically during the year as natural gas prices change.

Exhibit 9.51 shows the resources utilized to meet the design-peak day. Exhibit 9.52 shows the firm-peak-day demand distribution for the base simulation for the first plan year. Understandably, the design-peak day for Questar Gas is in the upper tail of the curve.

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[3] See the cluster analysis discussion in the Modeling Issues subsection of the Purchased Gas section of this report.

Base Case Identification

Whenever one draw of a stochastic analysis is identified as a base case, there is a general tendency to assume that there is a greater likelihood of all the attributes of that draw occurring than actually exists. Nevertheless, it is useful to identify a base case for ease of discussion and to facilitate the measurement of deviations.

In determining a base case, Questar Gas made available to the SENDOUT model, all of the optimal purchase gas resources selected to meet the design-peak day occurrence as described previously. Then, another Monte Carlo simulation was performed. Re-running the simulation allowed the model for each draw to size the appropriate level of purchased-gas resources from packages which, for the most part, will actually be under contract. Inevitably, when purchased-gas RFP responses are made, a few of the deals will fall through for a variety of reasons. These deals can usually be replaced under fairly similar terms.

There are a number of criteria, however, that could probably be used to determine a base case from the simulation. The draw with the median demand level could be used, for example, but that draw will not be the same as a draw with the median price for any one of the price distributions used and vice versa. Questar Gas developed an algorithm to systematically select its base case. Using the distributions for 21-year total cost, first year demand, first-year purchase gas and first-year cost-of-service gas, each distribution was ordered from least to greatest result value. Then, in the stated order above, starting with the median value, a window of draws was selected centered at the median. Those selected draws were then taken as the starting point to look in the second distribution with the same size matching draws. If matches were found, then those were taken to the third distribution as the starting point. The first draw that was found within the window and that existed in all distributions was selected as the base case. When no match was found from one distribution to the next, the process started over and the bounds of the window were increased to include the next highest and next lowest draws.

Purchased-Gas Resources

Exhibits 9.53 through 9.64 show the probability distributions for purchased gas for each month of the first plan year from the base simulation. Exhibit 9.65 shows the annual distribution from the simulation. Exhibit 9.66 shows the numerical monthly data with confidence limits. Purchased gas for the first plan year from the base case is approximately 45.2 million Dth. Questar Gas is confident that for a colder-than-normal year, sufficient purchased-gas resources will be available in the market. Likewise, Questar Gas is confident that in the event of a warmer-than-normal year, it has not “over-bought” base-load purchase contracts.

Cost-of-Service Gas

Another important output from the SENDOUT modeling exercise each year is a determination of the level of cost-of-service gas to be produced during the upcoming gas-supply year. Exhibits 9.67 through 9.78 show the distributions for cost of service gas for each month of the first plan year from the base simulation. Exhibit 9.79 shows the annual distribution from the simulation. Exhibit 9.80 shows the numerical monthly data with confidence limits. Cost-of-service production for the first plan year from the base case is approximately 70.1 million Dth.

First-Year and Total System Costs

The linear-programming objective function for the SENDOUT model is the minimization of variable cost. A distribution curve for first-year total cost from the base simulation is shown in Exhibit 9.81. The first year total cost from the base case is approximately $634.86 million. A similar curve for the total 21-year modeling time horizon is shown in Exhibit 9.82. The base case cost for this time period is approximately $11.03 billion.

Gas Supply Plan

Exhibits 9.83 through 9.86 show additional planning detail for the first two years of the base case. Monthly data for each category of cost-of-service gas and each purchase-gas package are listed. Also included are injections into and withdrawals from each of the four storage facilities utilized by the Company. Although no actual gas-supply year will ever perfectly mirror the plan, these exhibits are among the most useful products of the IRP process. They are used extensively in making monthly and day-to-day nomination decisions.

One of the drawbacks of the base case, as well as all stochastic scenarios, is the lack of normal temperatures for an entire year. This issue surfaced as the Company worked on data for its rate pass-through cases. The Rate Department requested that a report be included in the IRP that showed numbers associated with a normal temperature scenario. For this reason, the Company has decided to include this case which should not be confused with the base case. In this document, the normal temperature scenario can be seen in normal case Exhibits 9.87 and 9.88.

Gas Supply/Demand Balance

Exhibits 9.89 and 9.90 show monthly natural gas supply and demand broken out by geographical area, residential, commercial and the non-GS categories of commercial, industrial and electric generation.

This report is available in SENDOUT and is called “Natural Gas Requirements Versus Supply.” The data in these exhibits represent the selected base case. The SENDOUT report has been slightly adapted to show geographical areas and lost-and-unaccounted-for gas. Because demand is measured at the customer meter and modeling occurs at the city gate, in years past the demand has been grossed up by the lost-and-unaccounted-for amount to model natural gas demand at the city gate. This year lost-and-unaccounted-for gas was modeled as a percent of the other demand classes and is shown as its own specific demand class.

Exhibit 9.89 of the report shows Requirements of the System. Those are specifically Demand, Fuel Consumed, and Storage Injection. This gives the total requirement at 131.92 MMDth for the Base Case. Exhibit 9.90 shows sources of supply which include purchased gas categories, cost-of-service gas, Clay Basin, and the Aquifers. The total supply is 131.92 MMDth for the Base Case.