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Integrated Resource Plan

Risk & Uncertainty Analysis Briefing

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Table of Contents

1 INTRODUCTION

Analyzing risk and uncertainty is certainly not a contemporary concept. The modern concept of risk is rooted in the Hindu-Arabic numbering system that reached the West nearly 800 years ago, however it was during the Renaissance period that serious study of risk emerged. Pascal, with the help of another brilliant mathematician named Pierre de Fermat, made the first breakthrough in probability theory in 1654, and by 1725 mathematicians were competing with each other to develop life expectancy tables used to determine the premiums of life annuities sold by the English government to finance itself. The marine insurance industry was flourishing by the mid 1700s, requiring the sophisticated use of risk analysis methods.

With the advent of new discoveries and mathematical methods, the world of risk analysis and assessment developed and matured. By 1875, regression analysis to the mean was discovered and brought with it the expectation of normal matters (distributions) regarding world states. Building upon these theories, in 1952 Nobel Laureate Harry Markowitz demonstrated mathematically why putting all your "eggs" in one basket is risky and unacceptable from a risk management perspective and why diversification is the key to risk mitigation. Markowitz's Modern Portfolio Theory (MPT) revolutionized Wall Street, corporate finance, and decision making under uncertainty, and remains a fundamental element of risk assessment and mitigation today.

Markowitz demonstrated that if we treat single-period returns for various securities as random variables, we can assign them expected values, standard deviations and correlations. Based on these, we can calculate the expected return and volatility of any portfolio constructed with those securities. Volatility and expected return reflect proxies for risk and reward. Out of the entire universe of possible portfolios, certain ones will optimally balance risk and reward. These comprise what Markowitz called an efficient frontier of portfolios, and investors or decision makers should select a portfolio that lies on the efficient frontier. This frontier can be plotted as a risk/reward matrix that demonstrates the risk (plotted on the y axis) and reward (plotted on the x axis). Portfolios can then be plotted against each other to visually observe the risk/reward trade-off that Markowitz demonstrated mathematically.

Since Markowitz introduced MPT, others have expanded the application to include leverage and risk-neutral methods but the principals of MPT provide a broad context for understanding the interactions of systematic risk and reward. It has profoundly shaped how institutional portfolios are managed, and the mathematics of portfolio theory is used extensively in financial risk management and was a theoretical precursor for today's value-at-risk measures.

For the purposes of assessing optimal resource portfolios, the concept of the risk-reward trade-off is altered slightly to a concept of trading off the risk of a portfolio with the expected cost of the portfolio. The application of risk measurement techniques is greatly complicated by the issues confronted in electric markets, and sophisticated mathematical analyses are required to sufficiently quantify the ambit of risk arising from the myriad of situations impacting the risk vs. cost decisions encountered in the development of an optimal resource portfolio.

2 DEFINING RISK, UNCERTAINTY, AND EXPOSURE

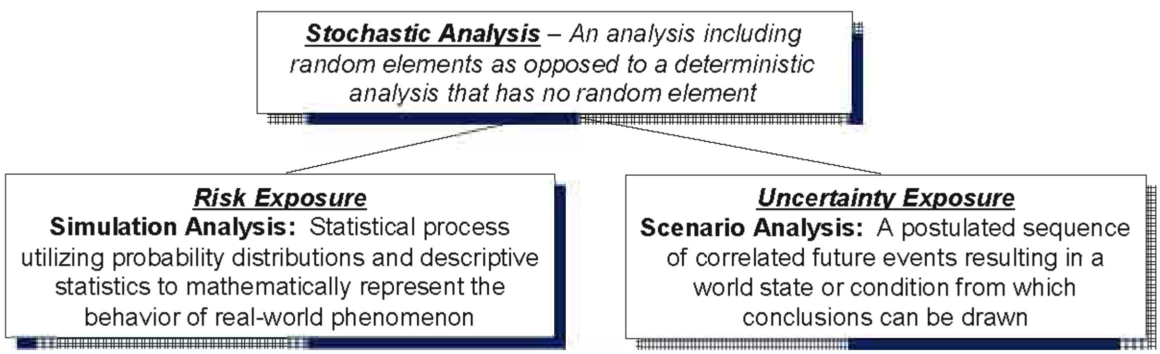
For purposes of developing the risk framework applied to AmerenUE's Integrated Resource Analysis, some definitions are appropriate. In his treatise entitled *Risk, Uncertainty, and Profit*, Frank K. Knight made perhaps the first distinction between risk and uncertainty, and this distinction is critical to the appropriate application of analysis tools and methods. Risk refers to situations where the decision-maker can assign mathematical probabilities to the randomness of outcomes faced. Uncertainty refers to situations when randomness cannot be expressed in terms of specific mathematical probabilities. Exposure is the extent to which a set of risks or uncertainties can bring hazard or harm. For the purposes of this analysis, AmerenUE is assessing the extent to which its resource options are exposed to risks and uncertainties.

3 ANALYSIS TECHNIQUES

AmerenUE employed three techniques in analyzing exposure to the risk and uncertainty of several resource expansion plans; these included simulation, scenario, and sensitivity analysis. Each method utilizes a different framework and processes to assess exposure to risk and uncertainty. In assessing risk we are interested in future values given our assumptions about the future, which are treated as random. To model these, we specify a stochastic process based upon a time series of the variable(s) we are interested in modeling. The word stochastic means random, and a stochastic process is a set of random variables that are ordered with respect to time. If time or variables take on integer values, the process is a discrete process. If it takes on real values, it is a continuous process.

For some world states, a continuous process is optimal since the variables can take on an infinite number of ranges (e.g. natural gas prices), whereas in others the range is discrete (e.g. a carbon tax will/will not be assessed). Both circumstances require a stochastic method to describe risk and uncertainty, as illustrated in Figure 3.1:

Figure 3.1
Stochastic Analysis for Risk and Uncertainty



There are multiple frameworks through which stochastic analysis can be applied. One method involves "decision tree" analysis, which seeks to demonstrate potential outcomes given the random movement of key variables. Although founded upon probability theory, tree analysis has a crude probability representation and affords minimal descriptive statistical parameters. Additionally, it does not utilize correlated variables and as such is not representative of "real-world" or continuous systems. Other numerical methods such as the Black-Scholes model can provide important insights into valuation, but fall short in providing detailed descriptions of risk and uncertainty and require complex volatility term structures to evaluate long duration (e.g. 20 year) analyses.

Simulation has replaced numerical solutions (or closed-form solutions) as a superior analysis technique and is a preferred method for assessing risk. Simulation allows a large number of individual iterations to be randomly generated through perturbation of key variables formulaically, the results of which are calculated and tabulated for each iteration. Results, rather than being presented on an individual or deterministic basis, are presented in terms of frequency distributions and statistical descriptors, providing summary statistics describing the aggregation of multiple outcomes based upon specified parameters.

Until the recent proliferation of high-speed computer technology, it was too time-intensive and analytically difficult to perform simulation analysis to a level that would sufficiently support a comprehensive risk analysis. Advances in computer technology have changed this, allowing large numbers of iterations to be simulated relatively quickly with the random movement of multiple correlated variables.

Since some randomness cannot be expressed through mathematical probabilities for uncertainties, sensitivity or scenario analysis is required. Scenario analysis represents the assessment of exposure based upon the discrete outcome of a particular world state, such as carbon legislation. Scenario analysis differs from sensitivity analysis in that more than one variable is perturbed, and through the subjective process of scenario development the random variables move in a correlated fashion (e.g. if a carbon tax is assessed, some coal plants will be replaced by gas plants, gas prices will rise, etc.).

Sensitivities represent discrete changes to individual variables to determine the impact on value or risk. Such changes may include varying the cost of new plant construction to determine the impact of on the portfolio value or electricity prices. Sensitivities are conducted through a deterministic or single-outcome methodology and can provide the means to bound risk within a specified parameter (e.g. high or low prices).

Both scenario and sensitivity analysis utilize a discrete process. For a discrete process, a deterministic or single-point estimate is applicable. A deterministic process implicitly reflects perfect information in the modeling process, with all variables and world states fixed and known, providing results that correspond precisely with the expected outcome of steady-state variables and conditions. As such, a deterministic or single-point modeling result reflects the anticipated outcome in light of perfectly executed and implemented assumptions.

Through the use of simulation analysis, scenario analysis, and sensitivity analysis, AmerenUE has performed a comprehensive stochastic analysis to quantify the exposure of various resource expansion plans to risk and uncertainty. The development of the parameters used in the stochastic process, and the analysis performed, are described herein. These parameters define the fundamental drivers that comprise the Integrated Resource Analysis.

4 APPLICATION OF STOCHASTIC AND DETERMINISTIC METHODS IN INTEGRATED RESOURCE ANALYSIS

As previously outlined, stochastic analysis is comprised of three primary components – a risk analysis, a scenario analysis and a sensitivity analysis.

- Risk analysis is used to assess the exposure of AmerenUE's candidate portfolios to mathematically describable randomness or volatility. Specifically, the risk analysis assesses the exposure of AmerenUE's candidate portfolios to randomness in commodity prices such as [redacted] as well as randomness in [redacted]

- Scenario analyses are appropriate when exposures to randomness cannot be described mathematically through probabilistic or statistical methods. A scenario analysis is different from a sensitivity analysis in that the scenario attempts to consider multiple variables in a correlated fashion without the benefit of statistical analysis. AmerenUE considered one scenario in its resource analysis – the potential for carbon regulation.

- Sensitivity analysis is used to "stress test" candidate portfolios. Sensitivity analyses represents a disconnect from potential real world outcomes as variables rarely move in isolation from each other. It can, however, be useful to the decision maker in providing insight into limits and provide a means of bounding potential outcomes. AmerenUE analyzed environmental compliance strategies, market depth, end effects and resource technology parameters in its sensitivity analysis.

Both stochastic and deterministic methods are utilized in each of these methods, as applicable to the specific objective. The following provides a high-level overview of the application of each method with respect to the Integrated Resource Analysis.

- Deterministic Analysis – This methodology is used to present the expected base-case costs of each resource portfolio. It summarizes the observations and performance of simulated portfolio operations and customer impacts.

- Simulated Risk Analysis – This methodology is used to demonstrate portfolio variability due to quantifiable risks. These parameters are numerically represented and reflect a statistical process and descriptors that are used to represent variability.

- Scenario Analysis – Scenario risks are also parameter driven. However the parameter variability cannot be reasonably represented by a known statistical process. Scenario analysis is used to assess abrupt changes in risk factors, such as introduction of high carbon allowance costs.

- Sensitivities – This methodology employs stressing different parameters such as AmerenUE's Environmental Compliance Strategy, Off-System Market Depth, technology parameters and evaluation of End Effects to evaluate the impacts of these variables on each resource portfolio.

5 SIMULATION ANALYSIS AND VARIABLE DEVELOPMENT

This section outlines assumptions, methodologies, and processes supporting the development of the risk parameters associated with the electric price forecasts. Wholesale prices are forecast on an hourly basis for the term of the investment horizon, and the risk parameters described herein characterize the price forecasts. The following subsections describe a build-up of processes and methods used to describe the risk profiles associated with each resource portfolio and resulting electric price forecast given the assumptions used, as well as the reasoning and development of the underlying assumptions that drive risk.

5.1 WHOLESALE ELECTRIC MARKET PRICE SIMULATION

The determination of an optimal generation resource portfolio is significantly influenced by the fundamental development of electricity forecast(s) of wholesale market prices. The commodity nature of a wholesale electric market anticipates that reasonable, well-informed parties will possess different market expectations and will participate in the market based upon these expectations. The challenge in determining the optimal generation supply mix is to determine a pricing path that best achieves the identified objectives, irrespective of achieving an exact match of market prices in the future. The model that AmerenUE utilizes to develop its fundamental wholesale electricity price forecast is MIDAS Transact, and the following provides an overview of the MIDAS electric price forecasting model. For a comprehensive overview of MIDAS, see the Electric Markets section of the Integrated Resource Analysis report.

5.2 MIDAS MODEL OVERVIEW

AmerenUE utilizes the MIDAS Transact electric market price forecasting model, an hourly, chronological wholesale market clearing price dispatch model that fundamentally develops prices that reflect specific inputs and data. The following represents the major characteristics of the modeling platform and the simulation variables required:

1. The central portion of the Eastern Interconnect (NERC regions including MAIN, MAPP, SPP, SERC, and ECAR) is modeled on an hourly basis for the term of the analysis, including all the loads, thermal unit data, and the interconnected transmission system transfer limits. Loads and resources are grouped according to the bulk system to represent known constraints and limits on electricity transfers.

2. Generation supply cost curves are developed for each load center based on fuel price forecasts, variable dispatch costs (e.g. variable O&M, emissions, etc.), and fuel conversion/efficiency rates. This curve represents a variable

cost supply stack of generation resources, stacked from lowest to highest dispatch cost.

3. The model determines an efficient dispatch and import/export of generation, respecting regional transmission limits and any wheeling rates, to minimize the cost to meet hourly demand on the system. The hourly market clearing price reflects the dispatch cost of the unit on the margin for each load center, given transmission and operational constraints.

4. Additionally, the model simulates the addition of various pre-specified economic new generation resources by technology in response to market prices. A new resource will be automatically added to the supply of resources when market prices are sufficient to recover the costs of that new resource, including capital recovery. If not capable of achieving economic new entry, the model will add resources to meet pre-determined reserve margin specifications.

5. Input variables driving the chronological, marginal cost dispatch within the model include all fuel price forecasts, variable O&M, emission costs, and escalation factors.

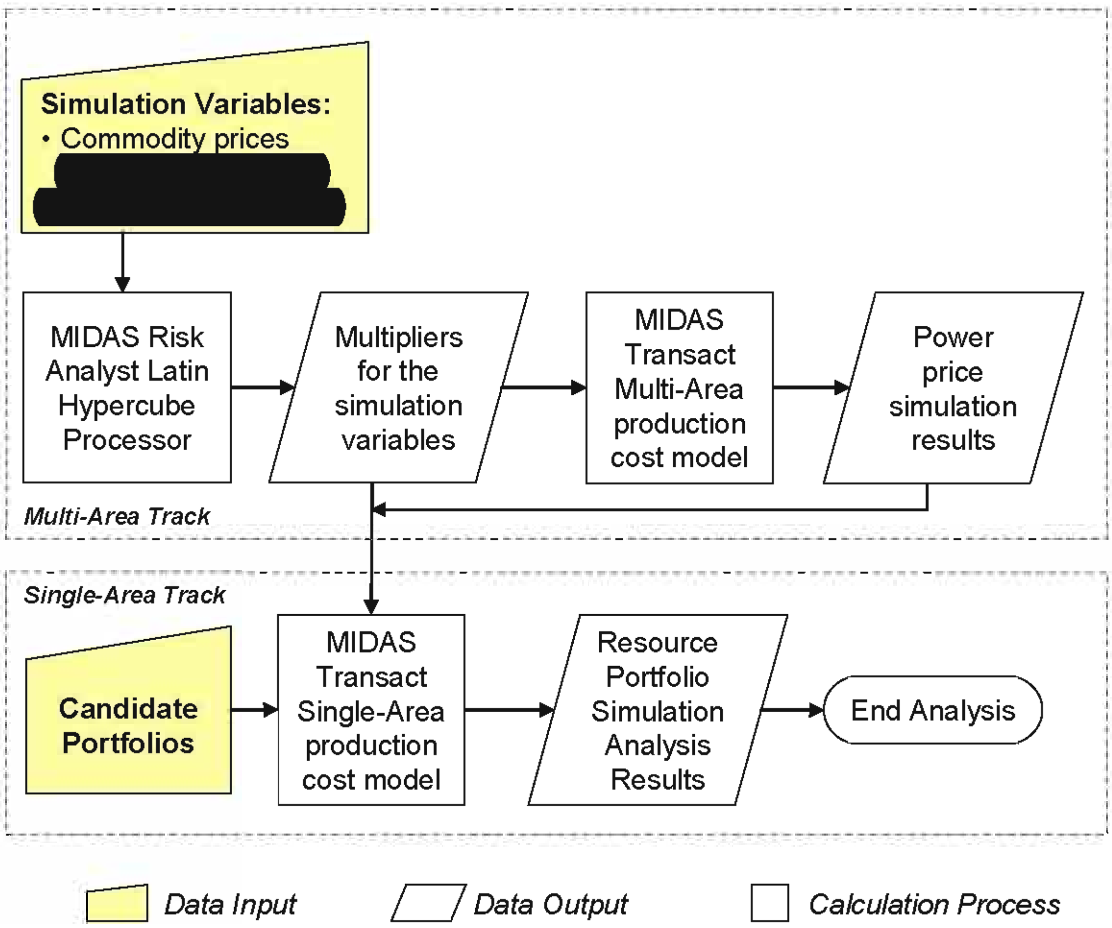
5.3 GLOBAL AND REGIONAL MARKET MODELING PROCESSES

AmerenUE utilizes the MIDAS Transact model for two separate tracks of modeling wholesale market clearing prices. A multi-area simulation of the broader market (the central Eastern Interconnect region) is performed, with common commodity and volatility assumptions. All units within the central Eastern Interconnect region are dispatched to meet hourly load on a marginal cost basis, constrained by the transmission system limitations and constraints. The purpose of developing a multi-area wholesale price forecast is to establish an hourly market "interface" price between the AmerenUE system and the interconnected system beyond the AmerenUE boarder.

The results of the multi-area modeling process, as reflected by an hourly wholesale interface market clearing price, are used as inputs to the single-area simulation of the AmerenUE system. The single-area simulation models the AmerenUE system characteristics and utilizes the interface price developed from the multi-area simulation to emulate economic purchases and sales with the broader market.

While AmerenUE utilizes global, generic unit assumptions in developing the multi-area price curves (to prevent bias and skewed results), the single-area simulation incorporates internal knowledge of the AmerenUE units and operational characteristics. Figure 5.1 below demonstrates the dual-track modeling process:

Figure 5.1
MIDAS Multi and Single-Area Modeling Tracks



5.4 DEVELOPMENT OF RISK PARAMETERS FOR SIMULATION VARIABLES

The MIDAS Transact Multi-area production cost model performs a chronological merit order dispatch of the generation supply stack to meet hourly load requirements for each modeled region, producing an hourly price forecast for each year of the valuation period. This price forecast represents a single, deterministic outcome based upon static input parameters, reflecting one of an infinite number of potential outcomes. While a deterministic price forecast provides meaningful information and valuable insight, it is limited in describing the risk characteristics associated with varying the key variables that drive price and determine risk.

To describe the risk associated with multiple variations of input parameters, and their respective correlated behavior, a set of multipliers are developed and incorporated into the MIDAS production cost modeling process to create multiple deterministic results.

The population of deterministic results represents the average or expected outcome and provides a distribution that quantifies and characterizes the risk associated with the average or expected results.

These multipliers are developed within the framework of the MIDAS Risk Analyst Module and represent the characteristics of each key input variable driving price and risk. A set of multipliers are stochastically developed, framed around defined parameters described herein, and used in the MIDAS Transact multi-area and single area runs to develop a set of deterministic modeling results, or endpoints, that are distributed around a mean. Each deterministic modeling run is simulated against an individual set of multipliers that are applied to the key input variables, providing a deterministic outcome that reflects the perturbing of key input variables.

There are five key input variables that are stochastically modeled within 10 stratified sampling points that define a distribution profile, producing 50 endpoints or discrete sets of multipliers that are used as inputs to the MIDAS Transact production cost modeling process. MIDAS performs 50 deterministic modeling runs, one run utilizing each discrete set of multipliers, to produce 50 deterministic modeling results that comprise the mean and distribution for a particular set of input assumptions. A comprehensive discussion of Risk Analyst and the development of the risk parameters and multipliers are described below.

5.4.1 MIDAS Risk Analyst Latin Hypercube Processor Overview

Risk Analyst is a product developed by Global Energy that is designed to be utilized with the MIDAS chronological dispatch model to forecast power prices and determine dispatch profiles when pre-specified risk parameters are incorporated into the simulation process. Risk Analyst utilizes a refinement of the Monte Carlo simulation methodology, Latin Hypercube, to develop a set of hourly multipliers that are utilized as inputs to the MIDAS chronological modeling process. These multipliers represent the application of stochastic parameters developed internally. A description of Monte Carlo methodology, and Latin Hypercube, are presented below along with a description of the descriptive variables that establish modeling parameters.

Monte Carlo Simulation

Simulation, as reflected within the context of the Integrated Resource Analysis, refers to an analytical method meant to imitate a continuous real-life system. Such methods are particularly effective when other analyses are too mathematically complex or too difficult to reproduce. Without the aid of simulation, a deterministic modeling methodology will produce a single outcome, generally the most likely or average scenario. Robust risk analysis seeks to analyze the effect of varying inputs of the modeled system, which requires the use of numerical simulation methods.

Numerical simulation methods known as Monte Carlo methods can be best described as statistical simulation methods, where statistical simulation is defined in quite general terms to be any method that utilizes sequences of random numbers to perform the simulation. Monte Carlo methods have been used for centuries, but only in the past several decades has the technique gained the status of a full-fledged numerical method capable of addressing the most complex applications.

The name Monte Carlo was coined because of the similarity of statistical simulation to games of chance. While the analogy of Monte Carlo methods to games of chance is a good one, the “game” within the context of applying this methodology is a physical electrical system of integrated and interrelated components, and the outcome is used to develop a solution to a risk-minimization problem.

Monte Carlo is now used routinely in many financial applications and is quite adaptable to analyses which involve the modeling of uncertainty through descriptive variables. Statistical simulation methods may be contrasted to conventional numerical discretization methods, which typically are applied to ordinary or partial differential equations that describe some underlying physical or mathematical system.

In many applications of Monte Carlo, the physical process is simulated directly, and there is no need to even write down the differential equations that describe the behavior of the system. The only requirement is that the physical (or mathematical) system be described by probability density functions and variables which will be discussed later in this section. A basic assumption underlying the use of Monte Carlo simulations is that the behavior of a system can be described by functions and variables, and once these are described, the Monte Carlo simulation can proceed by random sampling from the set of descriptive variables.

Multiple simulations are performed and the results are taken as an average over the number of observations. In many practical applications, one can predict the statistical error in this average result, and hence an estimate of the number of Monte Carlo trials that are needed to achieve a given error.

Assuming that the evolution of the physical system can be described by probability density functions and variables, the Monte Carlo simulation can proceed by sampling from this set of variables, which necessitates a fast and effective way to generate random numbers that are uniformly distributed. The outcomes of these random, or stochastic, samplings are compiled to produce and describe the result, but the essential characteristic of Monte Carlo is the use of random sampling techniques to arrive at a solution of a physical problem. In contrast, a conventional numerical solution approach would begin with the mathematical model of the physical system, discretizing the differential equations and then solving a set of algebraic equations for the unknown state of the system.

In light of this high-level definition of Monte Carlo, the process is defined by the major components of a Monte Carlo method. These components comprise the foundation of most Monte Carlo applications, and the primary components of a Monte Carlo simulation method include the following:

- *Probability distribution functions and descriptive variables* - the physical (or mathematical) system must be described
- *Sampling rules* - a prescription for sampling must be established, assuming the availability of random numbers on the unit interval. Risk Analyst utilizes a Latin Hypercube sampling process (discussed below)
- *Scoring (compilation of results)* - the outcomes must be accumulated into overall tallies or scores for the individual quantities being simulated
- *Variance reduction techniques* - methods for reducing the variance in the estimated solution to reduce the computational time for Monte Carlo simulation

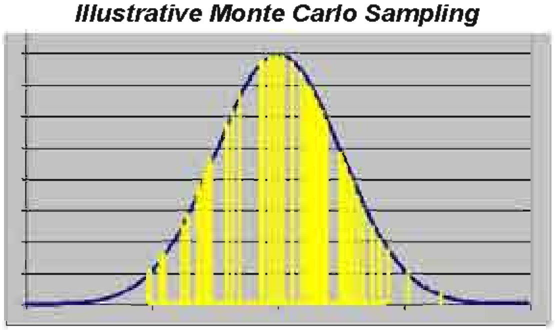
Latin Hypercube Sampling

Latin hypercube sampling (LHS) is a form of stratified sampling that can be applied to multiple variables. The method is commonly used to reduce the number or runs necessary for a Monte Carlo simulation and to achieve a "smoothing" of the distribution results. Pure Monte Carlo sampling does not guarantee a smooth distribution, and more draws are required to ensure a more definitive distribution profile. To ensure that samples are drawn across the entire distribution range and prevent "clustering" of results around limited ranges of the distribution, LHS can be incorporated into an existing Monte Carlo model fairly easily, and will work with variables following any analytical probability distribution.

The concept underlying LHS is to evenly divide the distribution into segments or strata, and perform random draws of variables within each of these pre-defined strata. Variables are sampled using an even sampling method, and then randomly combined sets of those variables are used for individual calculations of the target function. The sampling algorithm ensures that the distribution function is sampled evenly while maintaining the same probability trend. Figure 5.2 demonstrates the difference between a pure random sampling and a stratified sampling of a normal distribution.

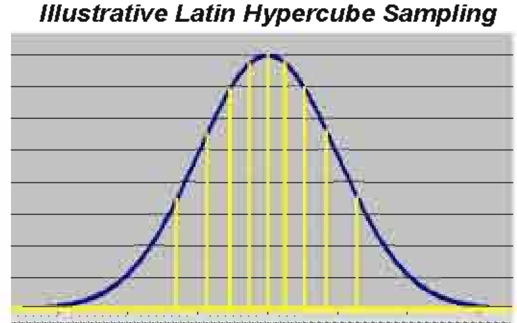
Figure 5.2
Random vs. Stratified Sampling of Distributions

Illustrative Monte Carlo Sampling



Uneven distribution resulting from random Monte Carlo sampling

Illustrative Latin Hypercube Sampling



Smooth distribution achieved through Latin Hypercube stratified sampling

To perform the stratified sampling, the cumulative probability (100 percent) is divided into segments or strata, one for each iteration of the Monte Carlo simulation. A probability is randomly picked within each strata using a uniform distribution, and then mapped to the correct representative value within the variable's actual distribution. AmerenUE utilized 10 strata for each of five simulated variables, representing a total of 50 sets of multipliers that are incorporated into the MIDAS chronological dispatch modeling process.

The use of Latin Hypercube sampling decreases the computational time required to perform Monte Carlo variable draws while capturing enough events across the distribution to ensure a comprehensive representation of potential outcomes. It ensures that results remain consistent with the descriptive distribution variables while achieving a smooth distribution that would otherwise require additional Monte Carlo simulations. Figure 5.2 above illustrates the sampling distributions inherent in the Monte Carlo vs. Latin Hypercube processes.

5.4.2 General Parameters Describing Simulation Variables in MIDAS Risk Analyst

The parameters used to describe individual variables within the Risk Analyst simulation process include time horizon, distribution type, variance methodology, and correlations. Each of these parameters will be discussed in greater detail. The parameters are used to describe the input variables that will be randomly drawn and reflected in the simulated results. As previously discussed, there are 5 simulation variables that were identified and determined to represent the key risk drivers: [redacted] For each of these variables, the simulation parameters reflect the characteristics and expectations of price behavior relative to the global attributes and expectations of each variable.

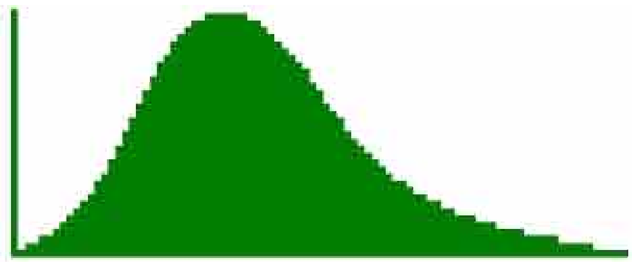
Time Horizon

Risk Analyst segments the timeframe of parameters into short-term (hourly), mid-term (monthly), and long-term (annual) time intervals for descriptive and modeling purposes. To reflect a meaningful amount of granularity, capturing seasonality and other observable attributes, a monthly time horizon was assumed for each variable in the simulation process.

Distribution Type

While there are multiple types of distributions that describe data and events, historical analyses of commodity price behavior reflect lognormal distributions of data. Lognormal distributions are observed in situations where values are positively skewed from the mean and cannot become negative. Commodity prices tend toward lognormal distributions since infrequent but extreme price spikes create tails that are positively skewed and commodity prices do not fall below a value of zero (for any significant period of time). AmerenUE utilized a lognormal distribution to describe the [redacted] Figure 5.3 is an example of the profile of a lognormal distribution.

Figure 5.3
Lognormal distribution Profile



Normal distributions are observed in natural phenomena where values are most likely to be clustered around the mean with marginal extreme values occurring equally to the right and left of the mean. The use of normal distributions to describe variables such as [redacted] and [redacted] reflects the reality that these estimates can move equally in either direction of their respective mean values. Figure 5.4 is an example of the profile of a normal distribution.

Figure 5.4
Normal Distribution Profile

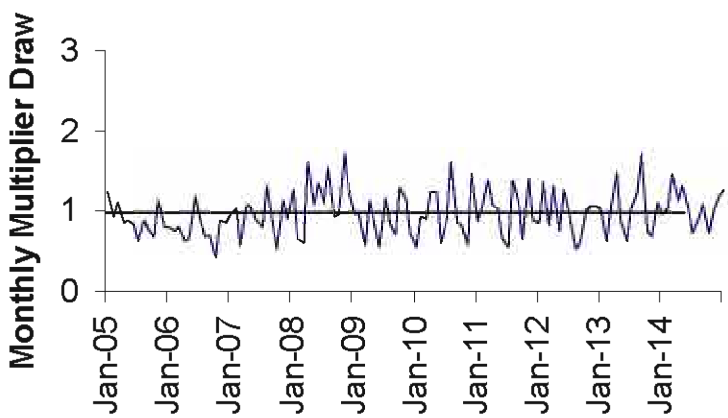
Variance Parameter Methods

There are three variance methods that can describe commodity prices; constant variance, random walk, and random walk with mean reversion. Each of these variance methods is discussed in detail.

Constant Variance

Constant variance reflects the standard deviation of the mean. For each random iteration, the draw starts at the mean value of the distribution and as a result there is no inter-period relationship between iterations. Values tend to fluctuate around the mean in a constant pattern over time, reflecting an equal probability of movement up or down (across the mean) over time but with no directional tendency. The resulting draws associated with constant variance tend to be generally choppy and are inconsistent with commodity price behavior over extended periods of time. Constant variance is most applicable for naturally occurring phenomena where the expected value is more likely to be closer to the mean than extreme values. [redacted] and [redacted] variances in the AmerenUE analysis have been reflected through the application of constant variance. Figure 5.5 demonstrates illustrative results of a single iteration utilizing a constant variance parameter:

Figure 5.5
Constant Variance Profile (Illustrative)

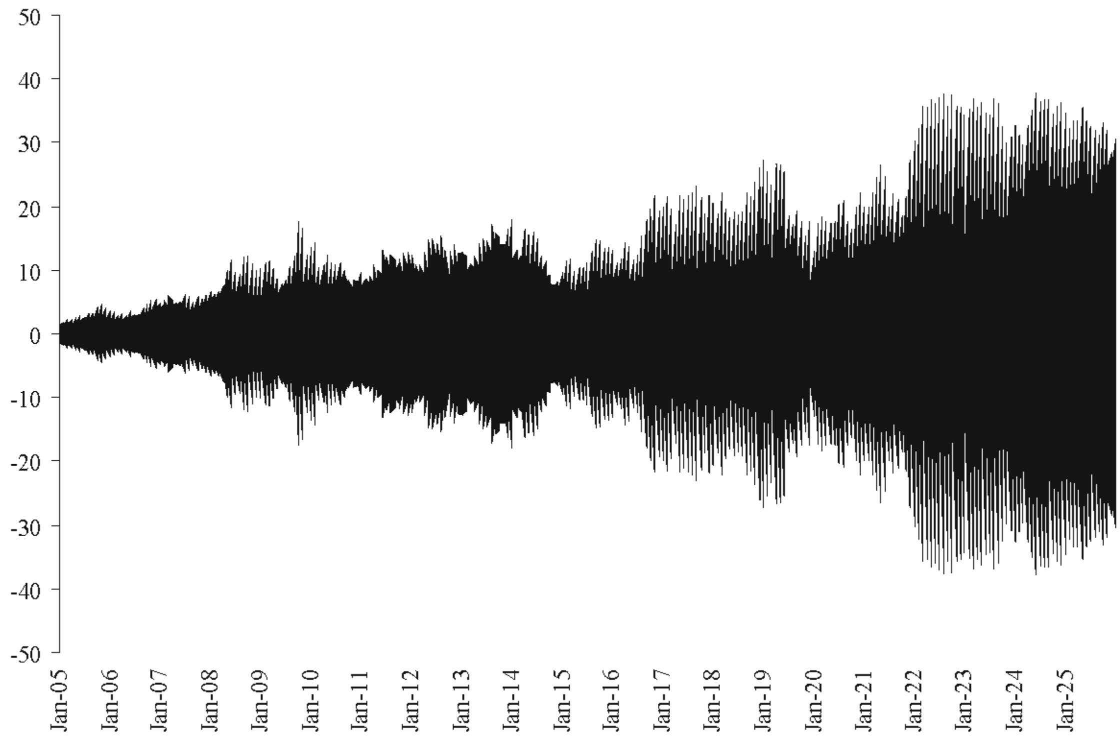


Source: MIDAS Risk Analyst, AmerenUE Analysis

Random Walk Variance

Random walk variance reflects the characteristics of Geometric Brownian Motion (GBM), where each iteration in the random draw process begins with the previous period value rather than the mean value. A GBM, or exponential Brownian motion, is a continuous-time stochastic process in which the logarithm of the randomly varying quantity follows a Brownian motion, or, perhaps more precisely, a Wiener process. It is appropriate in mathematical modeling of some phenomena in financial markets and is used particularly in the field of option pricing because a quantity that follows a GBM may take any value strictly greater than zero, and only the fractional changes of the random variate are significant. The chart below depicts the characteristics of GBM over time. As illustrated in figure 5.6, the variance continues to expand with time, reflecting the nature of a constant volatility assumption that compounds pricing results over time.

Figure 5.6
Illustration of Geometric Brownian Motion Price Profile



While this is precisely the nature of stock prices, it does not reflect the nature or historical behavior of commodity pricing. As such, the variation of commodity prices through time does not reflect the wide diffusion of variance over time that GBM demonstrates, but rather tends to follow a reversion to mean characteristic.

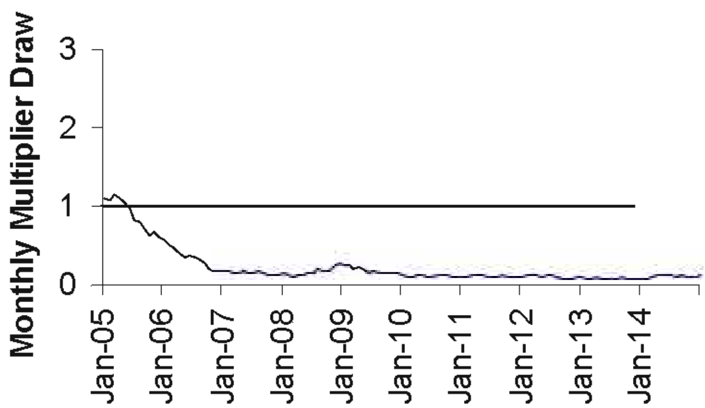
Random walk variance is demonstrated as calculated volatility, rather than as a standard deviation from the mean (constant variance). Volatility is a measure of uncertainty about the movement of a commodity over time, and is commonly stated as an annual number. The volatility of a commodity can be defined as the standard deviation of the return observed in one year when the return is expressed using continuous compounding. Volatility is the standard deviation of the natural logarithm of the price of a commodity at the end of one year, and is expressed as $\sigma\sqrt{\Delta t}$.

where σ is the standard deviation and t is the time interval

The MIDAS Risk Analyst module requires that volatility be input as an annualized standard deviation (of the relative change in values between time periods) as a fraction of the mean of the probability distribution when utilizing random walking parameters.

Due to its limitations and tendency to over-estimate the impacts of assuming constant volatility over time, AmerenUE did not utilize random walk variance parameters in its risk analysis. Figure 5.7 demonstrates an illustrative single iteration result under a random walk variance parameter. As illustrated, the next-period iteration begins at the previous iteration endpoint; creating a wide diffusion of results when multiple simulations are aggregated.

Figure 5.7
Random Walk Variance Profile (Illustrative)



Source: MIDAS Risk Analyst, AmerenUE Analysis

Random Walk with Mean Reversion Variance

Random walk with mean reversion reflects a variance parameter that seeks to incorporate the fundamentals of randomly occurring outcomes while staying within the framework of observable pricing behavior that is consistent with commodity market pricing.

In 1999, Robert Pindyck, Professor of Economics and Finance at the MIT Sloan School of Management, published a white paper in The Energy Journal entitled *The Long-run Evolution of Energy Prices*, in which he described his analyses of historical commodity price movements and recommended the use of mean reversion variance parameters in forecasting energy prices.

As the impetus for his work, Pindyck attempted to explain energy prices in structural terms, i.e., in terms of movements in supply and demand, and the variables that determine supply and demand. He found that structural models were not always useful for long-run forecasting, and as a result, forecasts of energy prices over longer time horizons are often no more than extrapolations in which prices are assumed to grow in real terms at a fixed rate. The rate of growth might reflect some notion of resource depletion and/or technological change, and could follow a random walk process with some drift.

Alternatively, prices could be assumed to revert to a trend line that grows or declines over time, which would be consistent with the notion that commodities are produced and sold in competitive markets, so that prices should revert toward long-run marginal cost which are likely to change slowly and predictably over time. This theory would imply that price shocks are only temporary and over sufficiently long time horizons prices are random walking and mean-reverting rather than just random walking.

According to Pindyck, whether such approaches to long-run forecasting are reasonable depends on the stochastic process that the price follows. He examined the long-run behavior of oil, coal and natural gas prices in the United States without any attempt at structural modeling, but rather focusing on alternative stochastic processes that might be consistent with this long-run behavior.

Pindyck demonstrated that the behavior of real energy prices suggests reversion to trend lines with slopes and levels that are both shifting continuously and unpredictably over time, so that each price follows a multivariate stochastic process. The shifts themselves may be mean-reverting, but ignoring them is misleading, and can lead to suboptimal forecasts. To accomplish this task, he examined the real prices of crude oil and bituminous coal over a 127-year period from 1870 to 1996. Natural gas data beginning in 1919 was also examined. For each resource, he fit the log real price series to a quadratic time trend, first using all of the data in the sample, and then using data only through 1960, through 1970, and through 1980.

In each case he ran a regression of the log price on a constant, time, and time squared interval. Each fitted trend equation was used to forecast prices through the year 2000. These fitted trend lines (and the resulting forecasts) move considerably as the sample period to which they are fit is lengthened. Furthermore, he found that although the magnitudes of the shifts vary, there is no single point in time for any resource at which shifts can be exclusively localized.

These findings suggest two basic characteristics of long-run price evolution. First, the log real price of each resource seems to be mean-reverting to a quadratic trend line, although the rate of mean reversion is slow, taking up to a decade to occur. Second, the trend line itself fluctuates as the sample is extended.

Rather than focusing on tests to determine whether or not prices follow random walks, Pindyck thought it may be more informative to address the extent to which price shocks are temporary or permanent. He found that variance ratio tests are informative in this regard, and such tests are based on the fact that if price follows a random walk, then the variance of k-period differences should grow linearly with k. On the other hand, if price follows a mean-reverting process, the variance of k-period differences will approach an upper limit as k grows, so that this ratio will fall to zero as k increases. More generally, the ratio provides a measure of the extent to which price shocks are persistent, or equivalently, the relative importance of any random walk component of price.

Although OPEC succeeded in pushing oil prices above competitive levels for periods of time, over the long run oil production has been largely competitive. The same is true for coal and natural gas. Pindyck indicated that he would expect the real prices of these resources to revert to long-run total marginal cost, i.e., a marginal cost that includes user costs associated with reserve accumulation and resource depletion. For a depletable resource such as oil or natural gas, he expects both the level of the log price trajectory and its slope to fluctuate over time in response to fluctuations in demand, extraction costs, and reserves.

Pindyck concluded from historic pricing data that for oil and coal any random walk component of a price shock is small, so that shocks are mostly transitory and indicates that this is consistent with a process in which price is slowly mean-reverting.

For natural gas, Pindyck found the results of using his model were somewhat inconsistent with both mean reversion and geometric Brownian motion processes. Pindyck suggests, however, that this pattern may simply reflect the shorter time series for these prices, along with the high degree of curvature of the quadratic trend line. He indicates that this is the case not so much because the earlier forecast data do not closely replicate more contemporary data, but more because the model does not describe movements in the trend lines for these commodities that are consistent with theory.

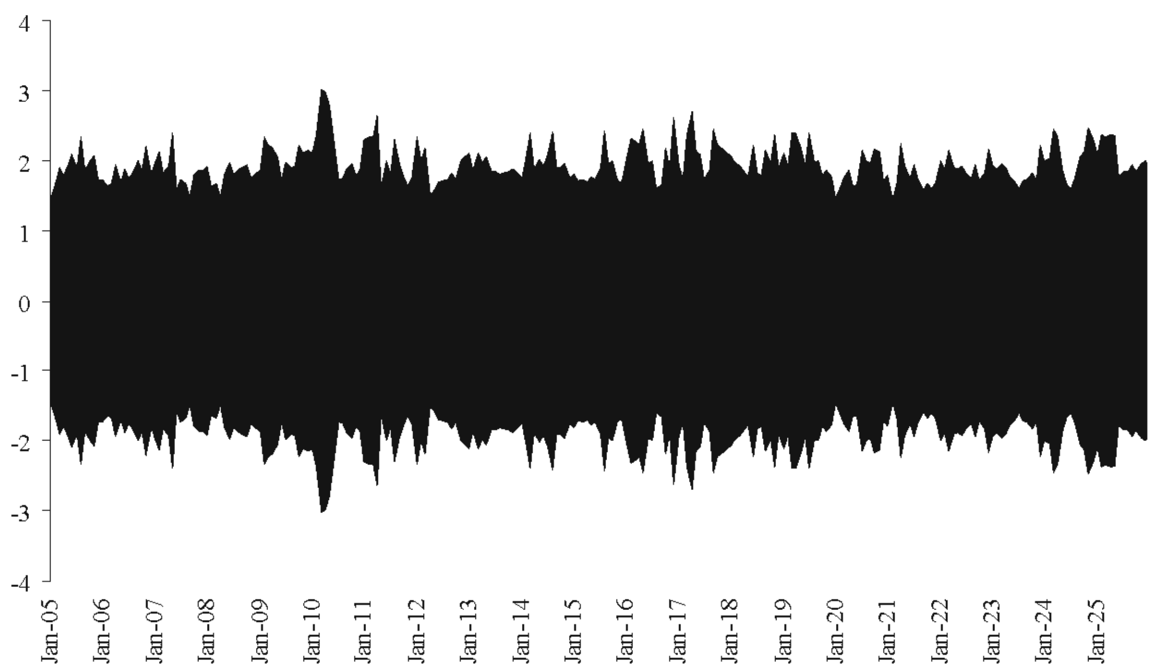
Pindyck also believed that the inconsistency for natural gas pricing is likely due to the sensitivity of a filtering process which he applied in the initialization, and found that by using a different sample period, he was able to produce estimates that yielded better forecasts and were consistent with a mean reversion process. He suggests that the difficulties experienced with natural gas pricing may be due to problems of initialization and the sensitivity of the estimates to the first few data points. His estimates are significantly improved for both coal and natural gas when slight modifications to beginning sample dates are used. As such, he emphasizes that the promise of mean reversion models derives largely from the fact that they capture in a nonstructural framework what basic theory tells us should be driving price movements and is supportive of their application in forecasting.

Pindyck also noted that the trend line to which price reverts, and which represents long-run total marginal cost, is itself unobservable. The parameters of the trend line at any point in time using data up to that point can be estimated, but those parameters will change over time. Therefore, if prices are forecast under the belief that they will revert to long-run marginal costs, he suggests that the marginal cost and its trend through time should also be estimated.

From his analyses, Pindyck suggests that a model forecasting long-run commodity price movement should incorporate two key characteristics: 1) reversion to mean production value which follows a trend; and 2) continuous random fluctuations in both the level and slope of that trend.

Approaching the issue from an option valuation perspective, Pindyck indicated that much of the literature on real options makes a rather convenient assumption that output price, input cost, or some other relevant stochastic state variable follows a Geometric Brownian Motion (GBM), a process in which the diffusion of prices continuously compounds over time (as previously discussed under the Random walking sub-section). He questions, however, that if the true process for commodities is a multivariate Ornstein-Uhlenbeck process (a stochastic process in which changes in time do not modify the probability or distribution, and is normally distributed), how far off might the process trend if only GBM is assumed? Figure 5.8 illustrates a stochastic process incorporating GBM with mean reversion, clearly demonstrating that variation within the framework of mean reversion eliminates the compounding effects of continuous volatility diffusion over time.

Figure 5.8
Illustration of GBM with Mean Reversion Price Profile



Pindyck cites analyses performed by other scholars who calculated call option values for stocks with prices that follow a trending Ornstein-Uhlenbeck process, and compared these to the values obtained from the Black-Scholes model (which is based on a GBM assumption). They demonstrate that Black-Scholes can over estimate the correct option value, however generally the size of the error is small relative to an acceptable error for financial option valuations.

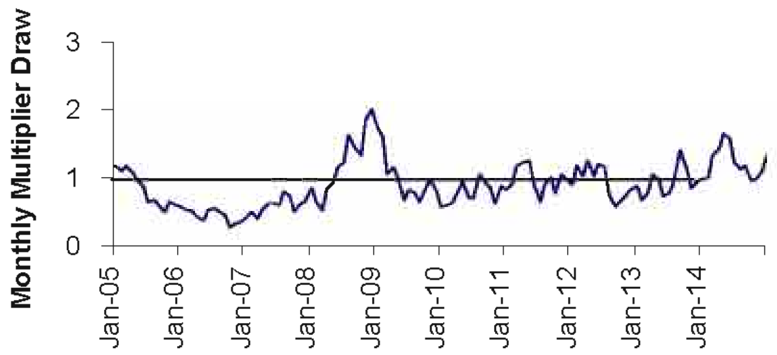
He also points out that their analyses did not attempt to determine the optimal exercise point, but rather the value of the option. Financial options typically have lifetimes of a few months to a year, while real options (such as generation resource portfolios) are much longer lived, therefore determining the optimal exercise point (the investment rule) is more important than valuing the option itself.

Pindyck solved for optimal investment rules when a fixed capital project follows a stochastic process. He considered mean-reverting processes as well as a GBM and showed that if the rate of mean reversion is fast, the optimal investment rule will depend strongly on the mean reversion value. The dependence is much weaker, however, if the rate of mean reversion is very slow. In the case of energy prices, the analysis indicated that the rate of mean reversion is slow, suggesting that for many applications, the GBM assumption may be acceptable when incorporated with a mean reversion process.

Pindyck concludes that, for irreversible investment decisions for which energy prices are the key stochastic state variables, 1) the GBM assumption is unlikely to lead to large errors in the optimal investment rule when combined with mean reversion assumptions and 2) the actual behavior of real commodity prices over the past century imply that forecasting models should incorporate mean reversion to a stochastically fluctuating trend line. The combination of GBM with mean reversion provides a solid framework in which to forecast commodity prices.

[redacted]

Figure 5.9
Random Walk with Mean Reversion Variance Profile (Illustrative)



Source: MIDAS Risk Analyst, AmerenUE Analysis

Variance Parameters Utilized in the MIDAS Risk Analyst Module

The MIDAS Risk Analyst module requires two parameters for modeling random walk with mean reversion: Volatility and a mean reversion rate.

Volatility

Volatility must be input as an expression of standard error as a percent of the mean when utilizing Random Walk with Mean Reversion variance parameters. The computation for volatility as input into the MIDAS Risk Analyst module, is:

STEXY / Mean of the Sample

where:

STEXY is an Excel regression function describing the standard error of X and Y where,

Y = absolute value of difference between the current price and the previous price
X = the previous price

For those inputs requiring a standard deviation input rather than volatility when utilizing Constant Variance variance parameters in the MIDAS Risk Analyst module, the computation reflects the calculation of standard deviation of the mean of historical prices and data, with the time interval being consistent with the data utilized for correlations. The calculation for standard deviation is:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - m)^2}$$

where σ is standard deviation of a data set

Mean Reversion Rate

The computation for the mean reversion rate reflects the negative of the slope of the regression of absolute price changes over previous price levels. The pricing values used to develop the mean reversion rates represent monthly historical settlement prices for the respective commodities which are applied in the Risk Analyst module on a monthly basis prospectively.

While volatility calculations are fairly straight forward, the mean reversion rates resulting from simple linear regression techniques can oftentimes reflect nonsensical results such as negative mean reversion rates, which can result from data inconsistencies, gaps, events, etc. As a result, a more sophisticated analytical approach is required to estimate the mean reversion rate. AmerenUE utilized a GARCH model for this purpose.

GARCH (Generalized Autoregressive Conditional Heteroskdasticity) is a sophisticated regression model that utilizes an iterative search procedure to maximize an objective function that solves for a mean reversion rate. While a simple linear regression model regresses only the price change against the previous price, the GARCH model is multivariate, incorporating the aforementioned regression of prices with a regression of the change in the variance against the previous variance. The GARCH model, estimation parameters, and application are presented below. Figure 5.10 reflects the GARCH algorithm, and Figure 5.11 illustrates the application of the algorithm in an Excel spreadsheet format:

Figure 5.10
GARCH Algorithm

$$\sigma^2{}_i = \omega + \alpha u^2{}_{i-1} + \beta \sigma^2{}_{i-1}$$

— Where u_i is the proportional change price between the $i-1$, as represented by

$$u_i = (P_i - P_{i-1}) / P_{i-1}$$

— Where $\sigma^2{}_i = v_i$ is the long run variance rate

The objective function must be maximized:

$$\sum_i - \ln(v_i) - u^2{}_i / v_i$$

Source: John C. Hull, *Options, Futures, and Other Derivatives*

Figure 5.11
GARCH illustrative application in Excel

Year	Month	Natural Gas P_i	Proportional Change u_i	Estimate of Variance Rate $v_i = \sigma^2{}_i$	Likelihood Measure $-\ln(v_i) - u^2{}_i / v_i$
1999	1	$1.85			
1999	2	$1.78	-0.038462		
1999	3	$1.77	-0.001408	0.00382797	5.5649
1999	4	$2.11	0.191537	0.00720629	(0.1581)
1999	5	$2.26	0.070076	0.00866470	4.1818
1999	6	$2.31	0.019912	0.01120322	4.4562
...	...	...	...	...	...
...	...	...	...	...	...
...	...	...	...	...	...
2004	12	$6.15	-0.065316	0.02245066	3.6064
2005	1	$6.14	-0.002207	0.02318232	3.7642
2005	2	$6.96	0.133102	0.02398756	2.9917
2005	3	$7.18	0.031667	0.02397566	3.6889
2005	4	$6.60	-0.080629	0.02463542	3.4397
					210.2210801

Trial estimates of GARCH parameters

ω	α	β
0.006227	0.02500	0.665232

Source: AmerenUE Analysis

Once the maximizing values of the GARCH parameters α, β, and ω are obtained, the mean reversion rate is equal to 1- α- β.

Correlations

The MIDAS Risk Analyst module allows risk variables to be correlated. AmerenUE engaged a comprehensive analysis of each input variable. There are five risk variables that are correlated in the stochastic simulation process: [redacted]

Comprehensive analyses of historical pricing data, along with an internal vetting process involving AmerenUE subject matter experts, provided the basis for defining the correlations and distributions supporting the development of the stochastic parameters utilized in the simulation process. A complete discussion of the development of correlations is presented in the Historical Data Analysis for Simulation Parameter Development section below.

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

Figure 5.12

[redacted]

Figure 5.13

[redacted]

[redacted]

[redacted]

[redacted]

Figure 5.14

[redacted]

[redacted]

Figure 5.15

[redacted]

[redacted]

[redacted]

Figure 5.16

[redacted]

[redacted]

Figure 5.17

[redacted]

[redacted]

[redacted]

Figure 5.18

[redacted]

[redacted]

[redacted]

[redacted]

Figure 5.19

[redacted]

Correlations

[redacted] were analyzed at various time intervals to determine correlations and trends in light of events and regulatory changes. Data were truncated at various intervals from the most current period backward to eliminate one-time events and pricing anomalies.

[redacted]

[redacted]

Figure 5.20

[redacted]

[redacted]

[redacted]

Figure 5.21

[redacted]

Figure 5.22

[redacted]

[redacted]

Figure 5.23

[redacted]

[redacted]

[redacted]

[redacted]

Figure 5.24

[redacted]

Figure 5.25

[redacted]

Figure 5.26

[redacted]

Figure 5.27

[redacted]

6 STOCHASTIC RISK PARAMETERS AND RESULTING MIDAS RISK ANALYST MULTIPLIERS

6.1 STOCHASTIC RISK PARAMETERS

Figure 6.1 depicts a summary of the simulation parameters that were developed utilizing the aforementioned methodologies and processes. The variance parameters and correlations are stated as annual values.

Figure 6.1
Summary of Stochastic Risk Parameters

Parameter	Time Frame	Distribution Shape	Variance Methodology	Variance Parameter(s)	Correlations
[redacted]					

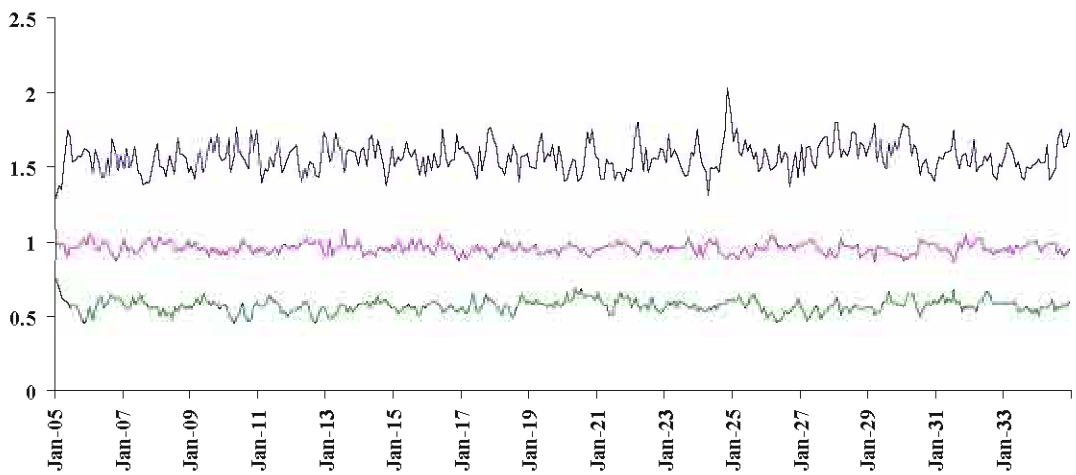
Source: AmerenUE Analysis

6.2 MIDAS RISK ANALYST MULTIPLIERS – RESULTS AND APPLICATION IN MIDAS TRANSACT

Figures 6.2 through 6.6 depict the profiles and percentiles (95%, 50%, and 5%) for the multipliers that were developed in the MIDAS Risk Analyst Latin Hypercube Processor incorporating the aforementioned stochastic parameters [redacted] The multipliers reflect fifty individual endpoints or sets of discrete multipliers for each simulated variable for each month of the study period. The resulting multipliers from the stochastic process are utilized as inputs to the deterministic modeling process described earlier in this report, thus providing an expected result and a distribution of ranges around the expected or mean results.

Figure 6.2

[redacted]

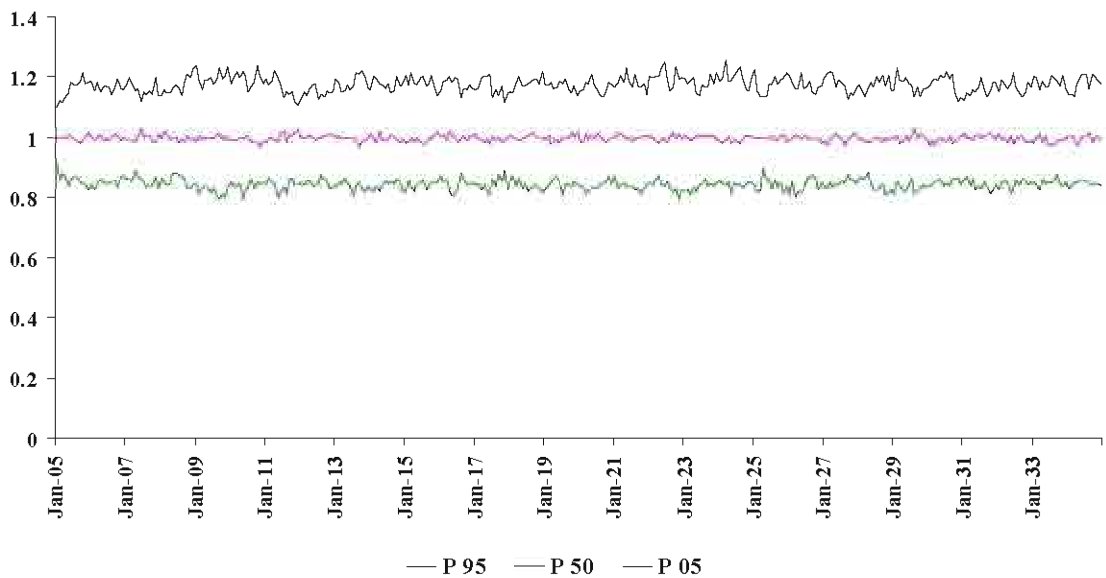


The [redacted] multipliers in Figure 6.2 represent the 95th, 50th, and 5th percentiles from the fifty endpoints that were developed in the MIDAS Risk Analyst Latin Hypercube process. The approximate ranges are between 2 and .5. An example of the application of these multipliers in the MIDAS Transact multi and single-area runs are as follows for a [redacted] The first run or iteration of the MIDAS run would multiply the [redacted] by the first set of multipliers, e.g. 1.7, for [redacted] for the first deterministic run. The MIDAS run would use this [redacted] for the applicable year of the simulation.

The second iteration would be multiplied by, say, .6, for a [redacted] applied to the second iteration and so forth through fifty iterations. As demonstrated by the multiplier ranges, for [redacted] the fifty MIDAS runs would reflect varying [redacted] between approximately [redacted] (multiplier of 2.0) and [redacted] multiplier of 0.5) at the 95th and 5th percentiles. The fifty iterations of MIDAS deterministic runs would represent the average of [redacted] perturbed through the stochastically derived multipliers.

Figure 6.3

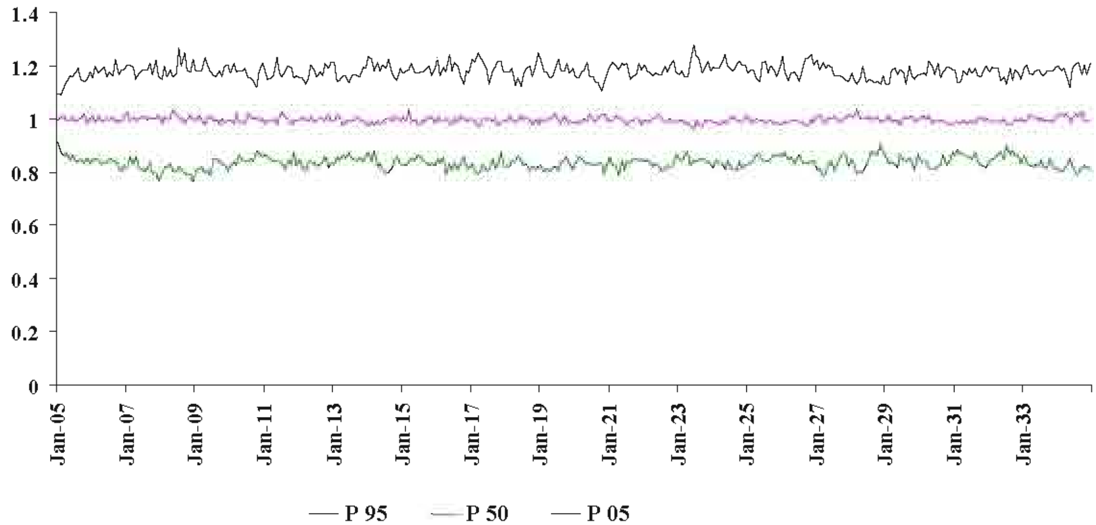
[redacted]



As illustrated with the [redacted] example above, the [redacted] multipliers in Figure 6.3 range from approximately 1.2 down to 0.8, thereby implying that, for example, for a [redacted] of [redacted] the range of [redacted] reflected in the fifty stochastic MIDAS runs would range between [redacted] and [redacted] (at the 95th and 5th percentiles).

Figure 6.4

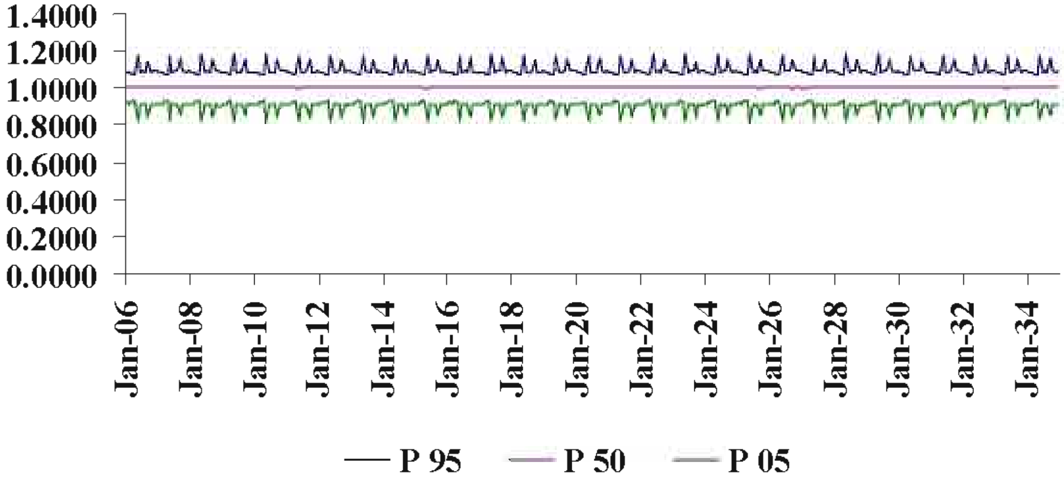
[redacted]



[redacted] the multipliers in Figure 6.4 range from between approximately 1.2 and 0.8. For example, if th[redacted] in a given year i[redacted] the ranges of [redacted] represented in the fifty MIDAS deterministic runs would be between $1,080/ton and [redacted] The fifty MIDAS runs reflect [redacted] ranging from 120 percent of the average forecasted input price to 80 percent of the forecasted price, again for the applicable year and period being modeled.

Figure 6.5

[redacted]



The ranges in Figure 6.5 for [redacted] fluctuation across the fifty MIDAS runs are approximately 1.15 to 0.85 times the [redacted] for the applicable period (again, representing the 95th and 5th percentiles of multiplier ranges).

Figure 6.6

[redacted]

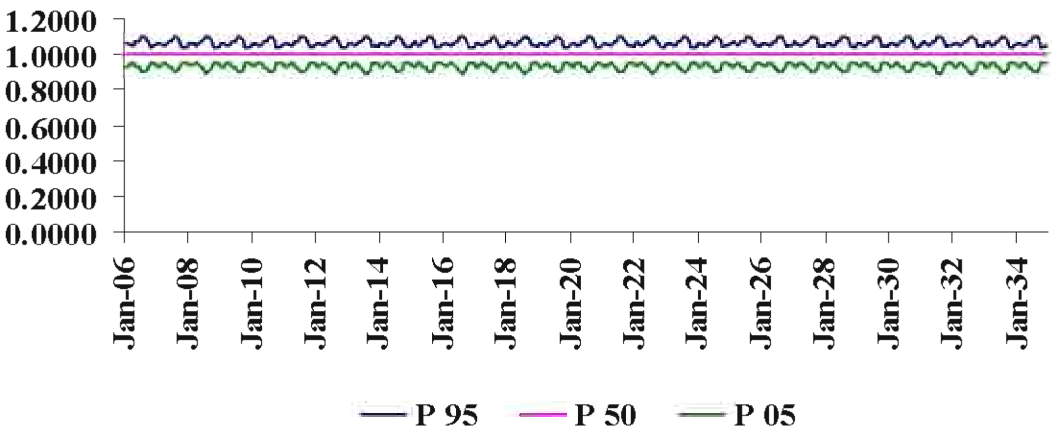
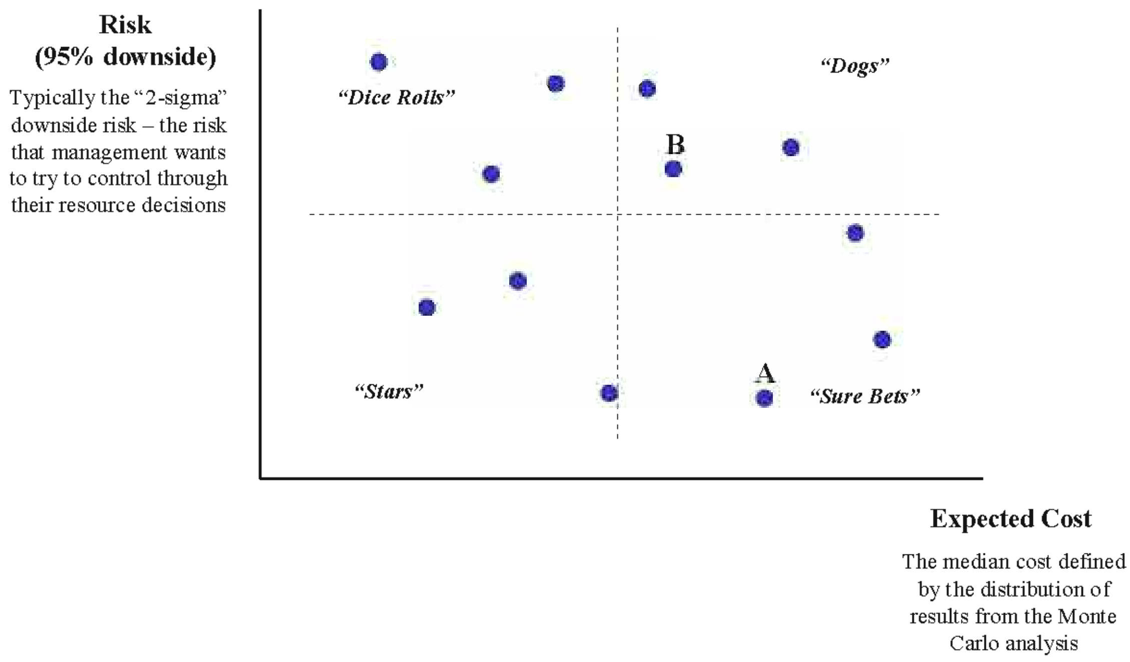


Figure 6.6 demonstrates tha[redacted] is slightly less than [redacted] ranging from approximately 1.1 to 0.9 times the applicable [redacted] for the applicable period being modeled in MIDAS Transact. The result reflects fifty deterministic runs with [redacted] ranging from 110 percent to 90 percent of the input [redacted]

6.3 INTERPRETATION OF SIMULATION ANALYSIS RESULTS

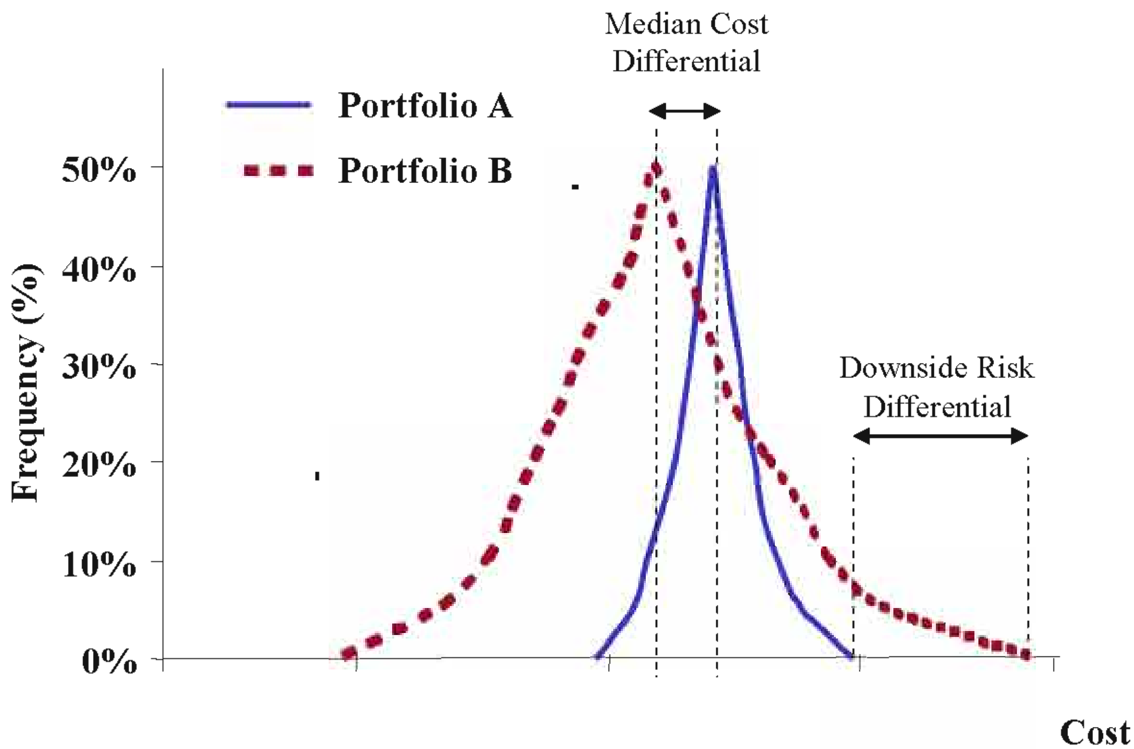
Toward interpreting the results of the simulation analysis, associated risk, and expected values, the results from the simulations can be plotted on a matrix demonstrating risk versus cost. Returning to the previous discussion of Modern Portfolio Theory, the matrix in Figure 6.7 below demonstrates the application of Markowitz's risk/reward trade-off, which has been modified to reflect a risk/cost trade-off perspective. In this illustrative matrix, results can be categorized into one of four quadrants described as 1) "Dice Rolls", which reflect low cost but high risk investments, 2) "Dogs," which represent high cost, high risk investments, 3) "Stars," which reflect low risk, low cost investments, and 4) "Sure Bets," or those investments that are high cost but low risk.

Figure 6.7
Risk vs. Cost Evaluation Matrix



Another way to evaluate simulation results is to chart the aggregate distribution of costs from multiple simulations and compare the "width" or variance of the distributions between each alternative. Figure 6.8 illustrates two portfolios reflecting different cost and risk profiles. In this example, while the average or median cost of Portfolio A is greater than Portfolio B, the risk profile of Portfolio A is much less than B. Said another way, Portfolio A's average cost may be higher, but the risk associated with Portfolio B is such that a significant probability exists for the cost of Portfolio B to exceed Portfolio A. The distribution around Portfolio A is much "tighter" than B, indicating that the variance of costs associated with Portfolio A is much less than B. In this illustration, if the downside risk differential (described here as excess cost) is such that management cannot accept this level of downside risk, the decision to go with Portfolio A will shield the company from the risk associated with Portfolio B, even though the average price of B is less. Portfolio A's cost is much more predictable than B, reflecting the objective associated with performing stochastic risk analysis; to reduce risk and uncertainty.

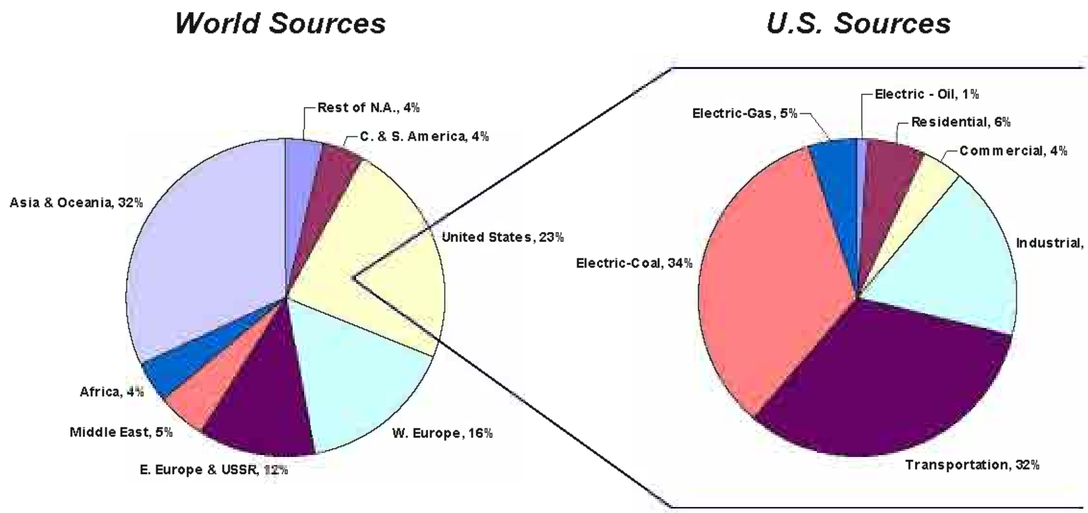
Figure 6.8
Illustration of Risk Variance between Sample Portfolios



7 CO_2 SCENARIOS

AmerenUE incorporated an environmental scenario into its Integrated Resource Analysis to determine the impacts of carbon legislation on the prospective resource portfolios under evaluation. Currently, U.S. electric generation resources account for less than 10 percent of world CO_2 emissions, as shown in Figure 7.1.

Figure 7.1
Global and U.S. CO_2 Sources



Source: Energy Information Agency

In the United States, there is currently no federal CO_2 regulation in place although increasing pressure from the grassroots and state government levels, as well as implementation of CO_2 policies in foreign countries, could result in future federal CO_2 regulation. While the federal government has yet to promulgate national CO_2 emission restrictions, multiple states, legislators and other nations are moving ahead with carbon regulation. Massachusetts and New Hampshire have already promulgated CO_2 regulations at the state level, and many states in the Mid-Atlantic and Northeast region are developing a regional CO_2 emission reduction program under the Regional Greenhouse Gas Initiative (RGGI) process. A bi-partisan proposal from Senators McCain and Lieberman calling for economy-wide CO_2 emission reductions received 43 votes in the Senate, and Senator Carper also included a CO_2 cap in his Clean Air Planning Act (CAPA) multi-pollutant proposal.

Internationally, the EU is proceeding with implementation of the Kyoto Protocol and Canada and Europe are moving ahead with programs aimed at participating in the Kyoto Protocol process.

At the corporate level, some utility companies have issued reports to address shareholder concerns about climate change and the risks associated with regulatory intervention and compliance. As a result of an agreement with shareholders, AEP had an independent sub-committee of its Board develop an emissions assessment report in August 2004 to evaluate the company's plan to respond to future air regulations. Cinergy issued its "Air Issues Report to Shareholders" in December 2004, in which it committed to reduce greenhouse gases by five percent below 2001 levels by 2010-2012. In contrast, TXU issued a report on its emissions strategy in which it said that it was not taking action to reduce greenhouse gases absent state or federal requirements. Southern Company issued a report to shareholders in May 2005, in which it said that even if with a high SO_2 tax, its greenhouse gas emissions were not likely to fall substantially over the next 15 years and concluded that providing reliable electric power to meet growing demand is more important than cutting emissions.

These examples illustrate the uncertainty associated with future carbon legislation and compliance. In the absence of certainty around prospective CO_2 emissions regulation, AmerenUE developed a scenario to address the potential impacts of greenhouse gas regulation on its resource portfolio evaluation process. The following is a comprehensive description of the development process and results.

7.1 SCENARIO DEVELOPMENT METHODOLOGY

In order to determine the impacts of carbon legislation on prospective resource portfolios, AmerenUE engaged ICF Consulting, Inc. to develop a fundamental CO_2 forecast based upon a Cap and Trade regulatory environment post 2010. ICF developed an expected case which is representative of the scope, stringency and timing of an air regulatory structure that is likely to be realized under a regulated or legislated future. While it remains uncertain as to how key emissions will be constrained over the next decade, the reduction assumptions supporting the ICF study are within the range of those proposed by both EPA and legislators. High and low sensitivities were provided around the expected case, and AmerenUE's CO_2 scenario reflects the deterministic outcomes of all three scenarios.

Figure 7.2 depicts the resulting CO_2 price forecasts which were used as the underlying assumptions supporting the CO_2 scenarios.

Figure 7.2
CO_2 Forecast

[redacted]

Mild Moderate Stringent

Source: ICF Consulting, Inc.

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

[redacted]

Figure 7.4

[redacted]

Source: AmerenUE Analysis

[redacted]

[redacted]

[redacted]

[redacted]

[redacted] [redacted]

[redacted]

[redacted]

[redacted]

Figure 7.5

[redacted]

Source: EEI / NCI Analysis

7.3 PRICING RESULTS

Figure 7.6 below demonstrates the deterministic monthly average price results from the multi-area MIDAS model run (as reflected at the AmerenUE system interface, or South MAIN) for each CO_2 scenario modeled. [redacted]

Figure 7.6

[redacted]

Source: AmerenUE Analysis

8 SENSITIVITY DISCUSSION

Along with the CO_2 scenario which included various CO_2 allowance price sensitivities, AmerenUE performed additional sensitivities to quantify the risk and costs of resource portfolios under the following parameters:

- Off-System Market Depth
- AmerenUE's Environmental Compliance Strategy
- Technology Parameters
- Evaluation of End Effects

The following is an overview of the various parameters that were stressed pertaining to each sensitivity analysis. The results for each sensitivity are included in the Integrated Resource Analysis.

8.1 OFF-SYSTEM MARKET DEPTH

The depth of the market for off-system transactions has a significant impact on the optimal resource portfolio in light of value and risk. Assumptions regarding the prospective market depth that can be reasonably anticipated are crucial in accurately defining value and risk, particularly if a specific technology is predicated upon a highly liquid, and deep market structure in which excess generation is to be sold or if the technology relies heavily upon the market for purchases.

After the launch of the MISO energy markets in April 2005, a new dynamic was observed relative to off-system transactions. With all resources and load across the MISO footprint bidding into a central energy market, the market for AmerenUE off-system transactions expanded. Essentially, what was once a limited network of counterparties became a highly liquid market place perpetuated by the structure and mechanisms previously discussed. Since physical transmission curtailments were supplanted with economic incentives (congestion pricing) and the supply market became completely transparent (through bidding), the market for off-system energy transactions expanded.

While it has expanded, the market depth under the MISO is not unlimited. Physical congestion has essentially been replaced with economic interruption, which will create an economic limitation on the volumetric of energy delivered from any point on the system. With transparent locational marginal pricing (LMP) at each injection and delivery point on the system, purchasers of energy can quickly determine the economic benefits or detriments associated with their resource purchases and alter them as economics dictate. The MISO will continue to make changes to its market processes and rules that will impact how the market responds. Market participants are just now learning how to operate in the new market environment and will likely change their practices in the future as rules change and/or more information is available. In light of these issues, it is difficult to draw meaningful conclusions about the market's future behavior based on the first seven months of operation.

The addition or retirement of system resources will also impact energy flows and resulting congestion pricing, adding to the economic complexity and uncertainty of prospective energy transactions. Additionally, as joint dispatch agreements between ISO's are finalized, modified or abandoned, the implications of these outcomes will impact the amount of economic energy transactions that will occur within the market.

Although there is limited data to base assumptions regarding off-system transactions, the base modeled volumetric of potential off-system transactions moving from the AmerenUE system to the market reflects [redacted] These limitations acknowledge the observed increase in volumes transacted by AmerenUE after the MISO energy market commencement while recognizing that as volumes continue to increase, a point of economic indifference will result due to increased congestion costs and losses.

A market depth sensitivity was performed to evaluate the impact of increasing AmerenUE market transaction limits to reflect unlimited access to counterparties and supply sales. Under this sensitivity, the base off-system limitations described above were removed in the model and the AmerenUE system was integrated into the MISO under the assumption that there would be no congestion impacts resulting from the dispatch of any AmerenUE resource on the system and no transmission. Essentially, this sensitivity sought to demonstrate the impact of unlimited market depth for the AmerenUE resource portfolios under evaluation.

In light of multiple system and economic dynamics, AmerenUE acknowledges that unlimited market depth is not feasible and did not select this sensitivity to represent an expectation of future market depth. This sensitivity was developed to demonstrate an extreme boundary in the absence of modeling an infinite number of prospective system states, conditions and definitions. While the MISO has a transmission expansion plan in place, this plan represents an expectation of what transmission infrastructure will be developed under a single scenario. Multiple events can impact system dynamics and alter anticipated outcomes. Additionally, there are economic impacts of congestion pricing and losses that are not reflected in prospective transmission infrastructure changes.

Since it is impossible to identify these prospective system events or assign probabilities to actual occurrence, AmerenUE sought to model the most extreme case of unlimited market depth as a means to evaluate the impacts on its resource expansion plans, understanding that actual results will fall somewhere between what is currently observed and the extreme case.

8.2 AMERENUE'S ENVIRONMENTAL COMPLIANCE STRATEGY

In developing an environmental compliance strategy, a company can vary in its method of compliance, from one extreme to the other, or somewhere in between the extremes. At one extreme, the Company can choose to not install any new control technology and purchase all required allowances. At the other extreme the Company can choose to install new control technology on all uncontrolled units and sell any excess allowances. A more balanced approach lies in between the extremes. In a balanced approach the company may choose to do both: purchase some additional allowances and install some control technology. The compliance strategy should balance the capital and operating and maintenance (O&M) costs of the control technology to the cost of purchasing allowances.

AmerenUE performed an environmental compliance strategy analysis separate from the Integrated Resource Plan (IRP) process. The intent of that analysis was to develop a balanced, least-cost compliance strategy for AmerenUE. That analysis is ongoing; however interim results from it were included in the IRP analysis as an alternative to a total purchase strategy.

Technology was considered for controlling the following pollutants: sulfur dioxide (SO_2), nitrogen oxide (NO_x) and mercury (Hg). AmerenUE's existing coal plants – Labadie, Rush Island, Sioux and Meramec – are the primary locations where control technology would be considered.

Flue Gas Desulfurization (FGD) is the primary SO_2 control technology considered. There are two basic types of FGD equipment, or scrubbers -- dry and wet. Dry scrubbers are typically used for controlling SO_2 at facilities which use a low sulfur, PRB-type fuel. Wet scrubbers are typically used for controlling SO_2 at facilities that use a higher sulfur fuel or a range of fuels.

There are a variety of technologies to control NO_x. The least costly and lowest removal efficiency is the over fired air (OFA) system. A higher removal can be achieved from a selective non-catalytic reduction (SNCR) system but at a higher capital and annual O&M cost. Finally the highest removal efficiency can be achieved from a selective catalytic reduction (SCR) system but at a much higher capital cost although at a somewhat lower annual O&M cost.

Hg removal technology is still in the early stages of development. For this analysis the only technology considered was an activated carbon injection (ACI) system.

The purchase scenario assumed no new installations of any SO_2 and NO_x control technology. It did assume Hg controls would be installed. AmerenUE would be required to meet the lower caps specified in the CAIR regulations for SO_2 and NO_x. Thus, AmerenUE purchased sufficient allowances to offset any excess emissions relative to the lower caps.

The balanced scenario assumed installation of scrubbers for SO_2 control on the following schedule:

[redacted]

For NO_x control, the only installations assumed were an [redacted] system on [redacted] by [redacted] and [redacted] on [redacted] and [redacted] by [redacted]

These emission control technology installations would create an emission strategy which would place AmerenUE in a "near" self-compliant position for SO_2 and NO_x. For this build scenario, any excess emissions relative to the lower emission caps would be purchased. Any surplus allowances would be sold to maintain the same SO_2 and NO_x position for the two alternatives.

8.3 TECHNOLOGY PARAMETERS

Under this sensitivity, five base operational and capital assumptions were varied independently to determine the impacts on valuation and risk. These sensitivities included deviations to base capital and transmission installed costs, fixed and variable O&M costs, and effective forced outage rate (EFOR) assumptions. Figures 8.1, and 8.2 demonstrate the nominal (base) and variant parameters that define the sensitivities, in absolute values and percentage change from base assumptions:

Figure 8.1
Technology Sensitivity Parameters (absolute values)

[redacted]

(1) Costs for a 2013 in service date

Source: AmerenUE

Figure 8.2
Technology Sensitivity Parameters (percentage from nominal)

[redacted]

8.4 EVALUATION OF END EFFECTS

The revenue requirement calculations represented in the Integrated Resource Analysis results do not include an adjustment for capital life end-effects. The analysis period is 20 years, and most of the assets' lives extend well beyond the end of the analysis. This results in the higher-cost revenue requirements incurred in the early years of a capital addition's economic life to be included in the PVRR while the lower cost revenue requirements of later years being excluded.

Without some type of end-effects adjustment, the capital-intensive portfolio's PVRR will tend to show a relatively higher revenue requirement. While utilizing revenue requirements is reflective of future ratemaking impacts during the 20-year analysis period, it does not, by itself, provide absolute comparative economics needed to address the relative costs of long-lived assets.

A sensitivity for end effects was performed, which extended the analysis period from 20 year to 28 years (limitations and assumptions within the MIDAS model limited the simulation period to 28 years). Under this sensitivity, all load growth assumptions were removed from the model after 2025, and MIDAS was allowed only to build new resources to replace any retirements occurring after 2025. Removing the load growth assumption allowed AmerenUE to model system dynamics within the framework of a production cost methodology rather than performing an escalation of 2025 results.

All other assumptions including fuel inputs were assumed to escalate at the general rate of inflation, and the MIDAS model performed an hourly chronological dispatch of the system resources to serve load for the extended analysis period. The results add additional analytical rigor by capturing the dynamics of hourly load profiles, generator performance, and transmission limitations with respect to portfolio performance, and reflect significantly more detail beyond a simple escalation of 2025 results to determine end effects.