Bounding the Composite Value at Risk for Energy Service Company Operation with DEnv, an Interval-Based Algorithm

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Summary

Deregulation in the power industry drives competition. It also increases the risk of doing business. Therefore it is important to manage and assess the risk. Value at risk (VaR) analysis has been used in financial institutions to evaluate portfolios of assets for some time, but the application of the approach in the power industry has not been established. The VaR of serving customer demand using the energy purchased on the auction market is our focus. In this paper, the risks of the energy service company (ESCO) are identified and the contract specifications and the VaR reviewed. In describing the difference in the business environments between the power and financial industries, the VaR analysis that has been used in the financial industry has been remodeled to best describe the assumed deregulated power environment. The pros and cons of the VaR levels are presented. As a consequence of the the interval-based computational core of DEnv (Distribution Envelope Determination), results are validated with respect to two sources of potential error.

1. Given the cumulative distributions of random variables, a derived random variable which is an arithmetic combination of the given random variables will have a single defined cumulative distribution only if the joint distribution of the given distributions is fully defined. If the joint distribution is not defined, a verified characterization of the result will be envelopes bounding the space of cumulative distribution curves that correspond to the members of the set of all the possible joint distributions. Distribution Envelope Determination (DEnv) [14] provides those envelopes, so that uncertainty in results due to uncertainty about dependencies among model variables is bounded.

2. The distributions of input random variables can be discretized in DEnv in in order to avoid the problem of finding envelopes for arbitrary input distributions analytically. Discretization typically involves approximation, but DEnv can avoid this by bounding each input distribution with envelopes such that the discretized form of an input is a pair of envelopes enclosing it. (While the input distribution is likely to be a continuous curve, the envelopes are staircase-shaped.) This representation for the input curves propagates into wider envelopes around the space of possible result curves, because those envelopes bound the space of results not only with respect to different dependency relationships between the inputs (as described in the previous item), but also with respect to the space of curves consistent with the envelopes around an input.

Results are valuable because insufficient data are typically present to specify the relevant dependencies accurately.

1 INTRODUCTION

Calls for competition in the power industry, from the wholesale level to the retail level, have made deregulation an attractive option around the world. New market structures have been studied to search for a good one that can ultimately satisfy regulatory bodies, customers, and suppliers. One approach that has been tried is the brokerage system. To accomplish it, the vertically integrated utilities are converted into a horizontal structure. The framework of the energy market is shown in Sheblé [1]. Since the emphasis of this paper is on the value at risk (VaR) of serving customer demand, the energy service company (ESCO), which serves customers, is discussed while leaving the rest to reference [1].

The ESCO collects its revenue from the customers of the energy and ancillary services it provides. It can also act as a wholesaler, reselling electric energy to other ESCOs, generating companies, etc. To obtain the desired electric energy to serve its purposes, the ESCO may purchase it through the auction market, or utilize the reserves that it has accumulated through load management programs or ownership of generation units.

In the deregulated environment, customers are free to choose among ESCOs. In addition, energy purchased by ESCOs from the auction market bears the risk of market price fluctuation. These, from the demand factors to the supply factors, are risks that the ESCO has to take in the new market structure. Since deregulation will render governmental financial protection largely obsolete, risk management and assessment tools should be considered and applied.

Ng and Sheblé (2000 [2]) introduce the different risk management and assessment tools available to assist an ESCO. This paper emphasizes Value at Risk (VaR) analysis.

2 VaR ANALYSIS REVIEW

VaR is the maximum amount of money that may be lost on a portfolio over a given period of time, with a given level of confidence (Best 1998 [3]). Figure 1 shows the graphical representation of VaR. VaR calculations are important because exceeding an appropriately defined maximum loss would be a major or even irrecoverable blow to the company. Thus business decisions need to be made with the objective of keeping the probability of such a loss below a relatively low level of probability deemed acceptable. Consequently determining the probability of such a catastrophic loss should be done carefully and, for dependability, should be validated with respect to lack of knowledge about the dependencies among the variables factoring into the calculation.

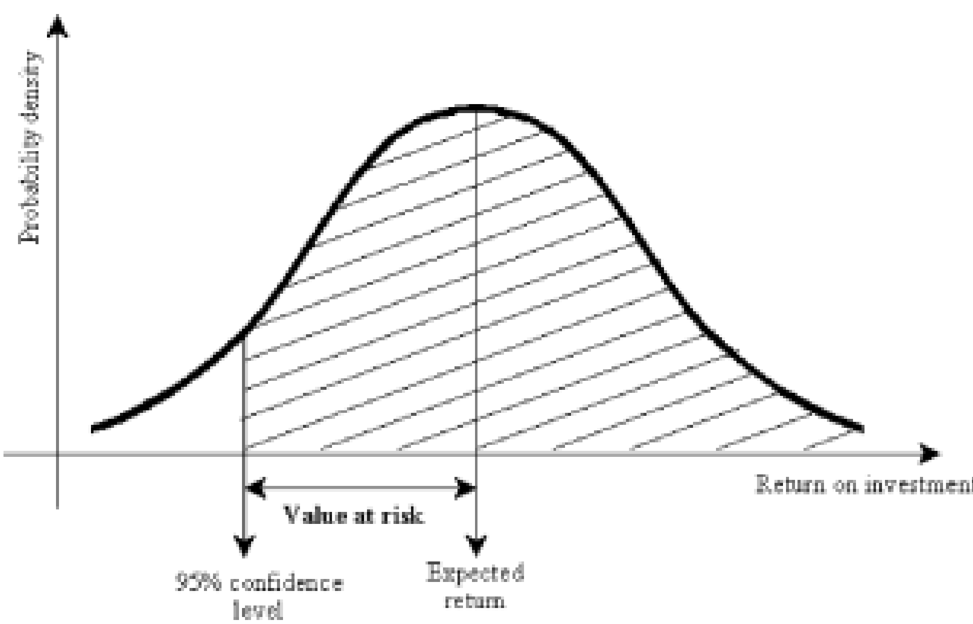

Figure 1. VaR at a given example confidence level.

There are currently three techniques that can be used to evaluate VaR of an ESCO. The first technique is historical simulation, which applies historical data to evaluate the VaR. The second technique is the covariance technique. To apply the covariance technique, the correlation matrix, C, of the uncertain factors is assumed available. The third technique is Monte Carlo simulation. Monte Carlo simulation involves artificially generating a very large set of events, from which VaR is derived [3].

The covariance technique is the easiest and fastest technique among the three. However, the technique assumes that the uncertain factors are normally distributed. Since normal distributions do not necessarily apply to all situations, the technique is consequently limited. Historical simulation and Monte Carlo simulation can supplement the covariance technique in such cases. Since historical simulation uses historical data to evaluate the VaR, there is no need to assume the form of the probabilistic distribution function of the uncertain factors. However, when historical data is limited, solving the VaR using the historical simulation method can be problematic. The Monte Carlo simulation method requires assuming the probability distributions of the uncertain factors (often that they are normal, but uncertain factors that are not normally distributed can be handled). For instance, in determining the VaR of holding option contracts (whose prices are not normally distributed), the option sensitivities (normally distributed) are used for the Monte Carlo simulation. Thus, the resulting VaR is able to consider option contracts [3].

Best (1998 [3]) describes the VaR resulting from asset price changes, the diversity of the portfolio (the number of assets with correlated price changes), and the holding position of the portfolio (the amount of money invested in a particular asset). This evaluation process is sufficient in a financial institution where the risk is primarily a result of price changes. To an ESCO, however, evaluating the VaR of the price changes is not sufficient. In addition to the risk of price fluctuation, there are two additional risks not described by Best. First, the customer demand and the deliverability of energy are uncertain, as there is a risk associated with the ESCO not being able to serve the customer with sufficient energy. For example, energy delivery can be prevented by transmission system failure, generation failure, etc. Thus an ESCO suffers the risk of contract violation by its supplier. Figure 2 shows the three components of VaR affecting a particular decision (such as amount of load management energy, number of contracts, purchased ancillary services, etc.) for an ESCO.

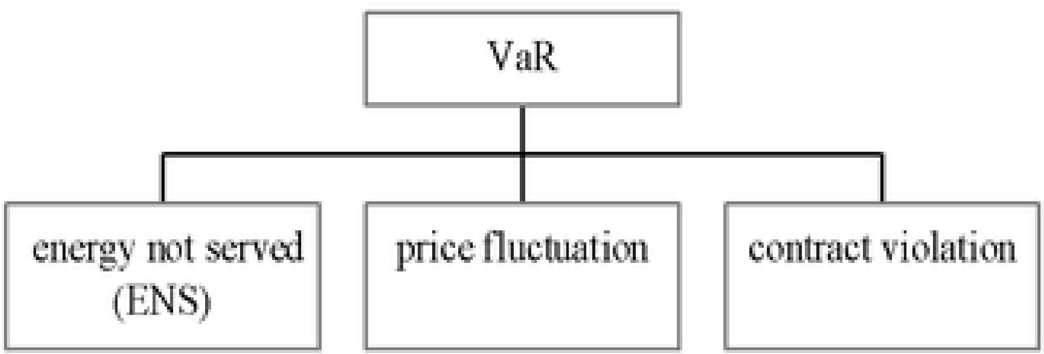

Figure 2. Factors in determining VaR of an ESCO.

3 PRICE FLUCTUATION VaR

To evaluate the VaR of market price fluctuation, the covariance matrix of the market price fluctuation is assumed to be available. Historical data may be used in determining the covariance matrix. Then, the VaR of market price fluctuation is evaluated using (1).

$$VaR = \lambda\sqrt{\boldsymbol{PCP}^t} \tag{1}$$

$\boldsymbol{P}$ is the proportion or position of the assets in monetary value. λ represents the degree of volatility and determines the confidence level. For instance, when $\lambda = 1$, the confidence level is 95% [3]. The covariance matrix, C, is determined using (2). Notation E in (2) denotes "expected value of."

$$C = \begin{vmatrix} \frac{E[(P_1-EP_1)(P_1-EP_1)]}{\sigma^2_{cP_1}} & \cdots & \frac{E[(P_1-EP_1)(P_n-EP_n)]}{\sigma_{P_1}\sigma_{P_n}} \\ \cdots & \frac{E[(P_i-EP_i)(P_j-EP_j)]}{\sigma_{P_i}\sigma_{P_j}} & \cdots \\ \frac{E[(P_n-EP_n)(P_1-EP_1)]}{\sigma_{P_n}\sigma_{P_1}} & \cdots & \frac{E[(P_n-EP_n)(P_n-EP_n)]}{\sigma^2_{cP_n}} \end{vmatrix} \tag{2}$$

Reference 11 shows the steps in evaluating VaR due to market price fluctuation.

In our presentation and full paper we will describe the remaining two major components of the ESCO value at risk, which are energy not served and contract violation. Background information on the the electric power industry will also be provided, emphasizing the ESCO as needed to support the discussion. Combining the three VaR components in a validated way that bounds uncertainty in results due to unspecified dependencies among the distributions describing the values of the three components, will be accomplished through Distribution Envelope Determination (DEnv) [14]. This is needed because the dependency relationships among the probability distributions for the three VaR components are not well understood. The output of DEnv will be used to bound the value at risk given a desired confidence level, or to bound the confidence level given a value at risk.

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