Spring 2008

Formulating hedging strategies for financial risk mitigation in competitive U.S. electricity markets

Karthik Viswanathan

FORMULATING HEDGING STRATEGIES FOR FINANCIAL RISK MITIGATION

IN COMPETITIVE U.S. ELECTRICITY MARKETS

by

KARTHIK VISWANATHAN

A THESIS

Presented to the Faculty of the Graduate School of the

UNIVERSITY OF MISSOURI - ROLLA

In Partial Fulfillment of the Requirements for the Degree

MASTER OF SCIENCE IN SYSTEMS ENGINEERING

2008

Approved by

David Enke, Advisor

Cihan Dagli

Badrul Chowdhury

ABSTRACT

In the competitive electricity industry, there exists some level of price risk for electricity in the form of price volatility. In order to perform efficient risk mitigation, it is necessary to have a good understanding on the future electricity demand and volatility. Electricity demand forecasting which drives the demand for fuels is first discussed. A method to predict future demand levels of electricity using a single factor mean reversion model is proposed. GARCH (1, 1) model is then used for forecasting the future daily volatility in demand. Both models use historical data for their simulations. The models, analysis methodology, data, and numerical results are discussed in this thesis. Modeling and simulation of risk is a key part of systems engineering. A risk mitigation framework that incorporates two cross-hedging strategies for reducing power price risk is proposed. The first strategy is a financial hedging strategy that involves taking one position in the cash market and an opposite position in the futures market. The second strategy involves the hedging of a physical delivery, which in this example involves taking two different positions in the electricity forward and natural gas futures markets such that the loss in one position will be offset by the gain in the other position. The risk is quantified in dollar terms for different risky scenarios, and the hedging strategies are simulated. To conclude, the two proposed hedging strategies are compared and the results of the mathematical modeling approaches are discussed in the final section The results indicates two key features: Hedging results in the stabilization of the expected profit margin and it also reduces the upward potential to profit from favorable market movements.

ACKNOWLEDGMENTS

I would like to express the deepest appreciation and thankfulness to my advisor and committee chair, Dr. David Enke, who taught me the financial engineering concepts and continually guided me to complete this research work. Without his guidance and persistent help, this thesis would not have been possible.

I would like to thank my committee members, Dr. Cihan Dagli and Dr. Badrul Chowdhury, for their support and assistance in the preparation of this thesis. In addition, special thanks are due to my student friends, who have helped me with their clarifications that I requested on the mathematical approaches and understanding of the subject.

I would like to thank the Intelligent Systems Center (ISC) of the University of Missouri – Rolla, along with the department of Engineering Management and Systems Engineering for their financial assistance.

I also thank my father and mother for their valuable moral support and encouragement to accomplish this thesis work.

TABLE OF CONTENTS

LIST OF ILLUSTRATIONS

LIST OF TABLES

1. INTRODUCTION

1.1. ELECTRICITY DEMAND AND VOLATILITY

The electricity generation process is very comprehensive and involves generation, transmission, distribution and retailing. Electric power can advance the nation's economic growth and productivity. Customers using electricity can be classified into three major groups: residential, commercial and industrial. The total demand for electricity in 2001 was 669,649 MW in the United States [2]. The demand is highest in the residential group (87.3%), followed by the commercial class (12.2%) with the reminder utilized by the industrial class (0.5%) [3].

While slightly under 13% overall, the forecasting of the electricity demand and its associated volatility is becoming necessary for companies in today's deregulated electricity market. It is essential for an electricity generating company to have an idea about future electricity demand levels. Based on the expected demand, the company might prefer to hedge electricity price risks and the associated uncertainty. Estimation of future volatilities is also useful for the calculation of Value-at-Risk (VaR), a commonly used metric for risk management [1].

In recent years, several techniques have been used to forecast electricity demand. For instance, the demand for electricity for a chosen heating system has been estimated using an ordinary least squares method [4]. ARIMA models and Fourier series models have been used to forecast half-hourly electric demand using simulation software [5]. Bayesian statistics has been used to test the functional form of US electricity demand modeling. Linear demand models, Log-linear demand models and the superior Trans-log demand models are described in the literature [6]. In addition to demand forecasting, electricity demand dynamics have also been studied in great detail [7]. Electricity demand is largely dependant on temperature variations. Smooth Transition and Threshold Regression models have been used to capture the response of electricity demand to temperature variations in the Spanish market [8]. These techniques do not explain the phenomena of mean reversion and heteroskedasticity observed in the electricity demand.

This study focuses on the single factor mean reversion and GARCH (1, 1) models. The mean reversion model captures temporary spikes in the demand level, which are often induced by extreme weather conditions. However, these spikes are not sustainable and they quickly revert back to the normal level within a few days. It is recognized that the demand function should consists of a deterministic and a stochastic variable. The evolution of the stochastic variable is described by the mean reversion model. The GARCH (1, 1) model is an extension of the Exponentially Weighted Moving Average (EWMA) model [1]. Both these models explain how historical data can be used to produce estimates of current and future levels of volatilities of the modeled variable. The EWMA model is a particular case in which the weights assigned to the previous data decrease exponentially as it is traversed back through time. The GARCH (1, 1) model uses a long-run average variance rate in addition to the variables used in EWMA model.

1.2. RISK MODEL USING CROSS-HEDGING STRATEGIES

Deregulation of the electricity industry has increased the level of price risks that the owners of electricity generators face. This increase in the level of price risk is due to increases in the level of price volatility. Prior to de-regulation, electricity price was determined by the regulators. Plant owners and market participants were not required to worry about price levels. Deregulation has brought in several private power plant operators. This has resulted in an increase in competition. The electricity demand and supply functions became stochastic, resulting in increased price volatility. As a consequence, risk management techniques have gained importance among electricity producers.

The three main sub-processes of systems engineering are Requirements Analysis, Functional Analysis and Allocation and Design Synthesis [13]. Risk management technique is a fundamental element within each of these sub-processes [14]. It is a continuous process of identifying, quantifying and mitigating risk. Mugurel et al. [15] presented a quantitative method for scenario based value, risk and cost analysis when proposing new systems architectures. Scenario based risk analysis methods provide an efficient way to model and simulate future risks. For instance, for an architect, who is either designing a new system or developing a new feature to integrate with the existing system, it is essential to have a good understanding about future risks in the early stages of architecting.

Risk management and mitigation techniques have been studied to a great extent. Several papers exist in the literature which discusses different strategies, algorithms and financial instruments for risk mitigation. S.J. Denga and S.S. Orenb [16] review different types of electricity financial instruments and highlight the roles of these electricity derivatives in mitigating market risks and structuring hedging strategies. Kaye, Outhred and Bannister [17] showed how forward contracts can be used to reduce the risk, while at the same time allowing for flexible responses to spot prices from the consumer's point of view. Thomas. W. Gedra [18] extends the idea of callable forward contracts and allows market participants to take advantage of flexibility in generation or consumption to obtain a monetary benefit, while simultaneously removing the risk of market price fluctuations. This work also considers the effects of strategic behavior on the part of market participants in their contract sales/purchase decisions. Genetic Algorithms (GA) were adopted by Lane, Richter and Sheble [19] in their research. The GA was used to find alternate valuations that are used to generate buy and sell signals. This approach was used instead of the Black-Scholes models due to the underlying assumptions required in the latter Black-Scholes model. These models incorporate direct-hedging using electricity forward contracts, which have low liquidity.

In this work, a risk mitigation framework which incorporates cross-hedging strategies to reduce electricity selling price risk is proposed. Two 'Cross Hedging' strategies, one as a financial hedge (not involving physical delivery of the commodity) and the other as a physical hedge (involving physical delivery), are discussed. Cross hedging uses futures contracts from two different markets. An example of using natural gas futures contracts to hedge the price risk in the power markets was pointed out by Andrews [20]. Eva Tanlapco et al. [21] describes the variance minimization approach for calculating the value of the hedged position and the amount of futures contracts that minimizes the risk for direct and cross hedging scenarios. Motivated by this work, the variance minimization approach is extended to study the actual dollar savings that results from the cross hedging. A modeling and simulation approach based on scenarios is used in this study.

1.3. NATURAL GAS FUTURES MARKET

Hedging using futures contracts is a strategy for mitigating risk. The world's first natural gas futures contracts were launched by the NYMEX in 1990. A natural gas futures contract is an agreement to buy or sell a specific amount of natural gas, at a specified future date called the delivery date, at a specific price called the futures price. Futures contracts, unlike forward contracts, are traded on an organized exchange (such as NYMEX). The rules and regulations of the exchange control the trading of the futures contracts. For instance, the clearing house of the NYMEX acts as an intermediary between the buyer and seller sees to it that the margin calls are met, and ensures that there is no credit risk for either of the parties.

The contract details that describe the futures contract are specified by the exchange [28]. One natural gas futures contract trades in units of 10,000 million British Thermal Units (mmBTU). The price is based on delivery at the Henry Hub in Louisiana and the nexus of 16 interstate natural gas pipeline systems. The pipelines serve the market throughout the US. The price is quoted in US dollars and cents per mmBTU. The mode of trading is "Open Outcry", conducted from 9:00 AM to 2:30 PM EST. The exchange specified mode of settlement is "Physical delivery", although in most cases the contracts are closed prior to expiration. The seller is responsible for the movement of the gas through the hub. The contracts are traded for delivery during any of the 12 months. Natural gas futures ("Contract-1") are for delivery during the subsequent calendar month. Trading stops three business days prior to the first calendar day of the delivery month.

This thesis is organized as follows: In section two, an overview of the competitive electricity industry is provided. The entire process of electricity generation and distribution is very complex and it involves market participants at various levels. A snapshot about the market and its participants is presented in this section. In section three, the description of the problem and the modeling approach to this problem are presented. In section four, a modeling technique for forecasting the electricity demand with a lead time of one month into the future is determined. The mean reversion model is used to forecast month-ahead electricity demand using the historical data. In section five, a modeling technique for forecasting the volatility in the electricity demand is discussed. GARCH (1, 1) model is used to forecast the volatility in the electricity demand using the historical data. In section six, cross-hedging strategies for financial risk mitigation are discussed. Two cross-hedging strategies are formulated for reducing the exposure to electricity price risk with a lead time of one-month. Natural gas futures contracts traded in NYMEX are used for cross-hedging purposes. The liquidity is very high in the natural gas futures market. Cross-hedging strategies are formulated using inputs from the electricity demand and volatility forecasts.

2. OVERVIEW OF THE COMPETITIVE ELECTRICITY INDUSTRY

2.1. DESCRIPTION OF MARKET PARTICIPANTS

After the deregulation of the utilities industry, a number of new market participants have appeared in place of old vertically integrated utilities. There are five categories of market participants discussed in this section. These categories are not mutually exclusive.

2.1.1. Generation Companies (GENCO). Generation Company refers to any firm which owns physical generation assets. These firms vary from very large deregulated subsidiaries to single plant independent power producers. The main objective of these companies is to maximize profit.

2.1.2. Load Serving Entities (LSE). Today end users are supplied electricity through bilateral agreements, or out of the wholesale market. Since buying electricity in the wholesale involves significant transaction costs, customers are generally served by intermediaries known as load serving entities. The functions of the LSE include estimating the aggregate demand of the customers and entering bids in the wholesale market to deliver power. LSE includes the competitive retailers (CR) that sell electricity at retail in the competitive market.

2.1.3. Power Marketers. Because of deregulation, there is a significant increase in the financial risk for both the generation companies and load serving entities. Most of the firms are not equipped to handle the risks. This led to the development of the new class of market participants known as power marketers. There are two fundamental components to this type of firm’s operation, the marketing and trading sections. The marketing section will approach GENCO, LSE and end users, offering to take part of the exposure associated with the electricity price. On many instances, the marketers pass on the risks to the trading section. Power marketers are equipped to handle the risk management aspect of the electricity supply. They have efficient trading operation procedures which minimizes the transaction costs. They have good knowledge about the trading and hedging principles using which they can hedge out the exposures arising out of uncertainty. The power marketers charge a premium for the risk management service. The transaction cost incurred is less since the transactions are performed in bulk.

2.1.4. Exchange and Market Makers. Utilities generally supplied electricity to a clearly defined geographical area, using a set of native generators to fulfill the demand requirements. To accommodate the increase in the market activity, a number of exchanges have emerged for the electricity industry. Exchanges match buyers and sellers of the electricity, and charge a small transaction fee for their service. There are several types of exchanges, differing in the contract time frame of delivery and trading of physical and financial commitments.

2.1.5. Independent System Operators. To encourage the physical safety of the grid, regulators have encouraged the formation of independent system operators (ISO). An ISO is a non-profit entity, which acts as a supervisor of the physical transactions registered between power suppliers and customers. The two main functions of the ISO are to balance power, and to manage congestion on the grid. The power balancing problem is due to the non storability nature of the electricity. The congestion management results from non-linear relationship between power injection and flows (to avoid overloading of transmission lines).

2.2. ELECTRICITY MARKETS

There are three fundamental markets available for trading electricity: the spot market (day ahead), the physical forward or bilateral market, and the financial futures market. In addition to these, there are a number of standard as well as over the counter options contracts traded, either through exchanges or on a purely bilateral basis. It is necessary to have a good understanding of the manner in which electricity is traded.

2.2.1. The Spot Market. Spot power is traded under a number of different market structures in the U.S., ranging from power pools to power exchanges to ISO. There are a set of rules governing a typical power exchange. While rules may vary somewhat based on the geographical location, it serves to influence the decision process facing producers in the deregulated marketplace.

A producer wishing to sell power submits a bid curve to the exchange. The bid curve describes the willingness of the producer to deliver power as a function of the market price. For example a producer may be willing to supply a total of 50 MW if the price is $20/MW and may offer to supply a total of 100MW if the price increases to $30/MW. Bid curves are generally supplied in a day-ahead basis.

The exchange gathers all the bids from the power producers, and similar bids from consumers. The bids are used to aggregate supply and demand curves for each hour. The intersection of the supply and demand curves determines the market clearing price (MCP). All supply bids with a price less than the MCP are accepted, and are paid the clearing price. Similarly all demand bids with a price higher than the MCP are accepted, and are charged the clearing price. This ensures that demand and supply commitments match perfectly and the exchange remains neutral.

2.2.2. The Physical Forward Market. Physical forwards can be traded on an exchange or in a bilateral manner through OTC transactions. Exchange traded forwards use standardized contracts. The contract specifies a single MW quantity and a single $/MWh price. The short position is obligated to deliver power physically at a constant rate to a location specified in the contract (the HUB). The short party is responsible for delivering the power from the generator location to the HUB, and that the long position is responsible for delivering the power from the HUB to the load location. For both the parties, this may involve purchasing additional contracts in the spot market. This purchase will not affect the price of the forward contract.

The price of exchange traded physical forwards is quoted daily by the exchange. The information includes the high and low prices as well as the volume traded and the open interest. The exchange quotes prices for every delivery month up to 15 months into the future. This vector of prices, which consistently evolve as new trades become public, constitutes the forward curve for electricity.

Physical forward contracts trade continuously while the exchange is open until the fourth business day prior to the first delivery day of the contract. At this point the trading terminates, and any party left with the short position is required to deliver power according to the contract specifications. A traded can avoid this by ‘closing out’ the short position before the trading termination date by taking a long position in exactly the same number of forward contracts for the same delivery month. For the ‘close-out’ to take place, the market should be high in liquidity. The liquidity of the electricity forward market is less than the natural gas futures market.

2.2.3. The Financial Futures Market. Financial futures contracts for electricity are traded on exchanges such as New York Mercantile Exchange (NTMEX) and the Chicago Board of Traded (CBOT). Financial contracts are similar to the physical contracts in structure. The main difference is that the parties entering into the contract are not interested in physically producing or consuming power, but rather use these contracts as a financial hedge in the market. The financial futures contracts are therefore settled by the exchange of the cash rather than power. The exchanges have two different approached for settling cash: ex-post settling and ex-ante settling. In the ex-post settling process, the futures contract is settled gradually during the delivery month for all the days in the delivery period. In the ex-ante settling, the futures contract is settled financially at its expiration date, i.e. on the fourth day prior to the beginning of the delivery period.

2.2.4. The Derivatives Markets. A number of options and other derivative contracts are traded in the electricity marketplace. They are generally grouped into three categories: temporal, locational and inter-commodity derivatives. Temporal derivatives are the most common, and are used to hedge against future movements in the spot price of power at a given location. Locational derivatives are generally used to hedge against the risk of volatile price spreads between the power production and delivery locations. Inter-commodity derivatives are contracts based on the price differential between electricity and another commodity.

The next section gives a description of the problem considered in terms of the unique nature of electricity and how it differs from other commodities. It is followed by the discussion on the modeling approach considered for this problem.

3. PROBLEM DEFINITION AND MODELING APPROACH

3.1. PROBLEM DEFINITION

The challenges currently facing participants in the competitive electricity markets are unique and staggering: unprecedented price volatility, fluctuations in the demand, a lack of historical market data on which to test the new modeling approaches, increased competition and continuously changing regulatory structure. Meeting these challenges will require the knowledge and experience of both the engineering and finance communities.

The fundamental difference between electricity and other commodities is the storability factor. For commodities which can be physically stored, future price risks can be mitigated using the 'cost-of-carry' and 'convenience yield' approaches. The role of arbitrage pricing theory (ABT) can be applied to storable commodities, by taking into account the spot and forward price differentials. Since electricity is not storable, traders cannot take advantage of the arbitrage pricing theory in order to perform electricity price risk mitigation. Therefore, hedging strategies which are widely used in equities market can be taken forward to perform risk reduction in the electricity market.

In the competitive electricity industry, there exists some level of price risk for electricity in the form of price volatility. Contracting exclusively in cash markets may leave electricity producers and purchasers exposed to price volatility, depending on contract terms. Contractual agreements are widely used in this industry, and are often based on the New York Mercantile Exchange (NYMEX) and Chicago Board of Trade (CBOT). Industry expansion is likely to heighten the demand for price risk management tools.

Electricity plant owners and purchasers of electricity may benefit from various techniques to manage price volatility. For electricity, however, no futures market is actively traded. The electricity forward market in NYMEX is in its nascent stage and is low in liquidity. Producers and purchasers of electricity may find cross-hedging electricity with natural gas futures contracts to be effective in reducing exposure to price volatility. The objective of this study is to estimate the cross-hedge relationship and strategies between spot electricity price and the NYMEX natural gas futures market for the cross-hedging horizon of one month.

In order for cross-hedging to reduce exposure to price volatility, the prices of the commodities being cross-hedged must be related, so that the respective prices follow in a predictable manner. In this study, it is determined that the price of natural gas has a positive correlation with the price of electricity. Moreover, the natural gas futures market has higher liquidity than the other futures and forward markets.

3.2. NEED STATEMENT

There is a need for an electricity generator company to minimize the exposure to selling electricity in the future. Numerous gas-fired electricity generation facilities exist across the US. About 70% of the facilities use natural gas as the raw material due to the clean burning nature of the natural gas feedstock. Deregulation of the electricity industry has brought in increased price volatility (risk). The owners of power plants must decide on strategies for managing the price risk. The major constraint they face is the uncertainty about future prices, which can potentially lead to loss of revenues.

3.3. MODELING APPROACH

This section describes the architecture of the modeling approach considered. The problem is sub-divided into three sub-sections. First, a modeling technique for forecasting the electricity demand with a lead time of one month into the future is determined. Second, a modeling technique for forecasting the volatility in the electricity demand is estimated. Input from the first model is used in the second model for forecasting demand volatility. Finally, inputs from these two sections are used to perform risk mitigation which forms the third sub-section. Two cross-hedging strategies are formulated for reducing the exposure to electricity price risk. Figure 3.1 indicates these sequential steps, which forms the modeling approach to this problem. The scope of the system is the existing electricity generation system in the U.S. The objective is to minimize the selling price risk associated with the electricity generation process for the plant owners. The price of the raw material (natural gas), plan operation cost, electricity price, and trading are within the scope of this work.

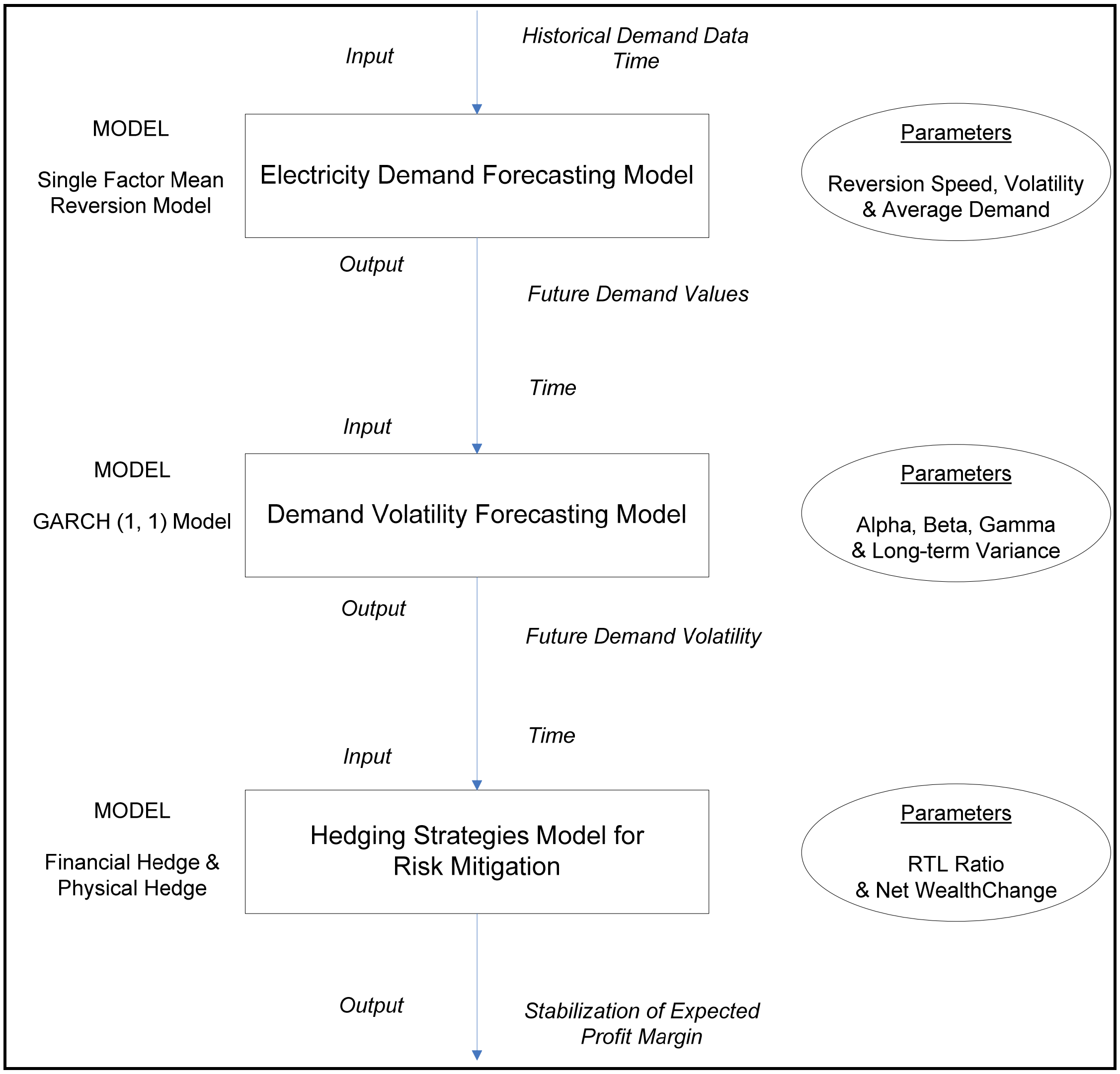

Figure 3.1. Depiction of the Modeling Approach

The next section discusses the electricity demand forecasting using the mean reversion model. The inputs to this model are the historical demand data and the time period. The parameters estimated are the speed of reversion, volatility and the long-run average demand. The output from this model is the estimate of the long-run average demand.

4. FORECASTING MONTH-AHEAD ELECTRICITY DEMAND

4.1. FORECASTING LONG-RUN AVERAGE DEMAND

4.1.1. Mean Reversion Model. In dealing with energy demand and prices, the limitations of Geometric Brownian Motion (GBM) exist, such that the demand or the price level has the tendency to drift without any bounds. A GBM model shows no consideration for the previous demand or price level. The probability of returning to the average long-run demand or price is minimal.

Seasonal effects are considered to be one of the most important parameters affecting the electricity demand level. For this research, the monthly seasonality will be modeled. For example, let L_m represents the monthly load variable. This is defined as the sum of deterministic and stochastic components, as given in Equation 1.

$$L_m = \mu_m^L + r_m^L \tag{1}$$

Within the equation, the deterministic component μ_m^L represents the average monthly load pattern. Each calendar month will have a separate deterministic component, which can be further used to capture the yearly seasonality. The stochastic component r_m^L of the monthly load pattern is needed to explain any deviation in the actual observed load from the pattern given by μ_m^L. In order to achieve this, the variable r_m^L has to contain as many random variables as there are days in that particular month.

For this research, the mean reverting model is used to explain how the stochastic component r_m^L evolves over time [9]. Mean reversion is the tendency of the load demand value to gravitate towards a normal equilibrium demand level. This is governed by the level of production, the level of demand caused by weather factors, the supply-demand equilibrium, etc. Let us suppose that the electricity demand on a particular day jumps from 20,000MW to 27,000MW due to an unexpected event such as a heat wave or an increased industrial activity. The probability of the demand to return to its average level once the cause of the deviation goes away is high. The electricity generators will eventually decrease production once the cause of the price jump goes away.

4.1.2. Methodology. Mean reversion is considered to be a modified form of the random walk process, wherein the changes in the demand level are not completely independent [10]. The mean reverting process is characterized by demand levels that have some degree of memory about previous demand levels. Mathematically the mean reversion can be represented as follows:

$$d_{t+1} - d_t = \alpha (d - d_t) + \sigma . \varepsilon_t \tag{2}$$

where

$d_{t+1} - d_t$	Expected change in demand at times (t+1) and (t)
d	Mean reversion or the monthly equilibrium level
d_t	Spot demand level
α	Mean reversion rate (speed of reversion)
σ	Volatility
ε	Random shock to the demand from t to (t+1)
$\alpha(d - d_t)$	Mean reversion component
$\sigma . \varepsilon_t$	Random component

The mean reversion component is governed by the reversion rate and the distance between the spot demand and the long-run equilibrium demand values. If the spot demand is below the mean reversion level, the mean reversion component is positive, resulting in an upward influence on the spot demand. If the spot demand is above the mean reversion level, the mean reversion component is negative, resulting in a downward influence on the spot demand. Over a period of time, this causes a drift towards the mean demand level at a speed determined by the mean reversion rate.

Figure 4.1 illustrates how the short-term spikes in the load (daily demand values) quickly revert back to the long-term mean value (monthly equilibrium demand level). The daily demand (spot) has a tendency to revert back towards the monthly average value. Since the fluctuations occur on a daily basis, the demand is never at an equilibrium level. The plant operator meets the surge in the demand by purchasing natural gas in the spot market. Temperature is one of the factors for a surge in the demand.

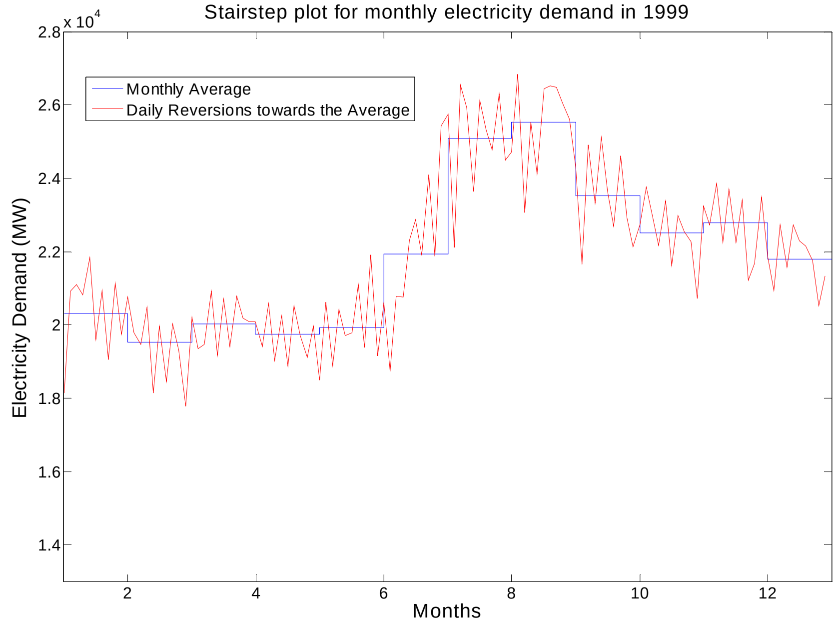

Figure 4.1. Stair Step Plot

For clarity, the mean value is modeled as a monthly average value. Instead of considering daily spikes in demand, averages of three-day demand values are considered. This means there will be 10 values (indicated by the spikes) for a month (clarity is reduced when daily demand values are considered). From Figure 4.1, it is inferred that after each spike there is a tendency to revert back to the mean demand level. The mean reverting model explains this phenomenon. However, since the market is never at equilibrium, the normal monthly level in itself can be considered a stochastic process. During 1999, the monthly average value is higher during the months of July, August and September. The spot demand drifts back to the mean demand level at a speed determined by the parameter mean reversion rate. Higher the distance between the spot demand the long-term average demand, greater is the mean reversion rate. It indicates faster reversion towards mean. This parameter, along with the long-term average demand and the volatility are to be estimated. The mathematical estimation technique is presented in the next section.

4.1.3. Mean Reversion Parameters Estimation. The various parameters to be estimated in the mean reversion model are the mean reversion rate, the volatility and the mean reversion level. These parameters can be easily estimated using the Microsoft Excel© built-in functions for STDEV, SQRT, SLOPE, INTERCEPT and STEYX. The negative of the slope gives the mean reversion rate. This simple and robust method is used by regressing the absolute demand value changes over previous demand values.

The technique for estimating the value of the mean reversion parameters is adopted from the energy price processes used for derivatives pricing and risk management [10]. In the calculation, the demand is annualized using 365 days per year. From the historical daily demand data, the percentage demand change and the actual demand change are calculated. Statistical regression analysis is used to estimate the parameters of the model. The SLOPE function uses the actual demand change against the previous demand. The rate of reversion parameter is the negative of the slope. The long-run mean demand is the ratio of INTERCEPT to the negative of the SLOPE. The volatility is the ratio of the residual standard deviation STEYX to the long-run mean demand.

4.2. DATA AND NUMERICAL RESULTS OF STUDY

4.2.1. Data. The electricity data used for this study are publicly available. The University of California Energy Institute (UCEI) sponsored a collection of data related to the newly restructured electricity markets in California. Data from this collection was used, representing the day-ahead market clearing prices and quantities in the Power Exchange (PX). The dataset for this study is comprised of data from April 1998 to December 2000. For the mean reversion model, 1999 data is used to estimate the values of α, σ, d . The estimated values are used in Equation 2 to forecast the demand for year 2000, i.e., time (t+1).

4.2.2. Mean Reversion Model Results. The parameters of the mean reversion model appear in Table 4.1 for the sampling population (training data). As an example of reversion and the use of the table, if the speed of reversion in January 1999 is 40.66% as shown in the table, the drift returns back to the mean level in (1/0.4066) = 2.45 days**.**

Table 4.1. Mean Reversion Model Parameters (Monthly)

Months	Speed of reversion	Volatility	Long-term mean demand (MW)
Jan 99	40.66%	5.20%	20,374
Feb 99	42.85%	5.15%	19,372
Mar 99	53.72%	4.75%	20,055
Apr 99	69.62%	5.33%	19,684
May 99	44.85%	6.40%	19,969
Jun 99	24.58%	6.57%	22,608
Jul 99	68.10%	8.11%	25,005
Aug 99	77.99%	6.76%	25,730
Sep 99	61.36%	5.69%	23,627
Oct 99	68.11%	4.87%	22,707
Nov 99	70.93%	5.46%	22,727
Dec 99	42.86%	3.83%	21,640

The parameters values from Table 4.1 can be used to predict day-ahead electricity demand. This study is interested in predicting month-ahead electricity demand. Therefore, yearly values of long-term mean demand, volatility and speed of reversion are required, as shown in Table 4.2. The speed of reversion is 23.94%, which means the drift in the demand reverts back to the mean level in (1/0.2394) = 4.17 months. The yearly volatility of 6.35% is pretty high, which is largely due to the seasonality influence.

Table 4.2. Mean Reversion Model Parameters (Yearly)

Year	Speed of reversion	Volatility	Long-term mean demand (MW)
1999	23.94%	6.35%	22,468

The yearly values from Table 4.2 and the current month's mean spot demand value are used as inputs to predict the month-ahead demand for the year 2000. Using the spot demand, the forward demand at time t+1 (1 month ahead) is forecasted using Equation 2.

The plot in Figure 4.2 compares the forecast against the actual demand values. The difference between the forecasted value and the actual value is high for the months June (6), July (7) and December (12). This model would have tracked the demand spikes better if a bigger dataset is available for training. The actual average demand during December 1999 is considerably higher than that in December 2000. Since the parameters are calculated using December 1999 data as the training population, the forecasted value is higher than the actual value during December 2000.

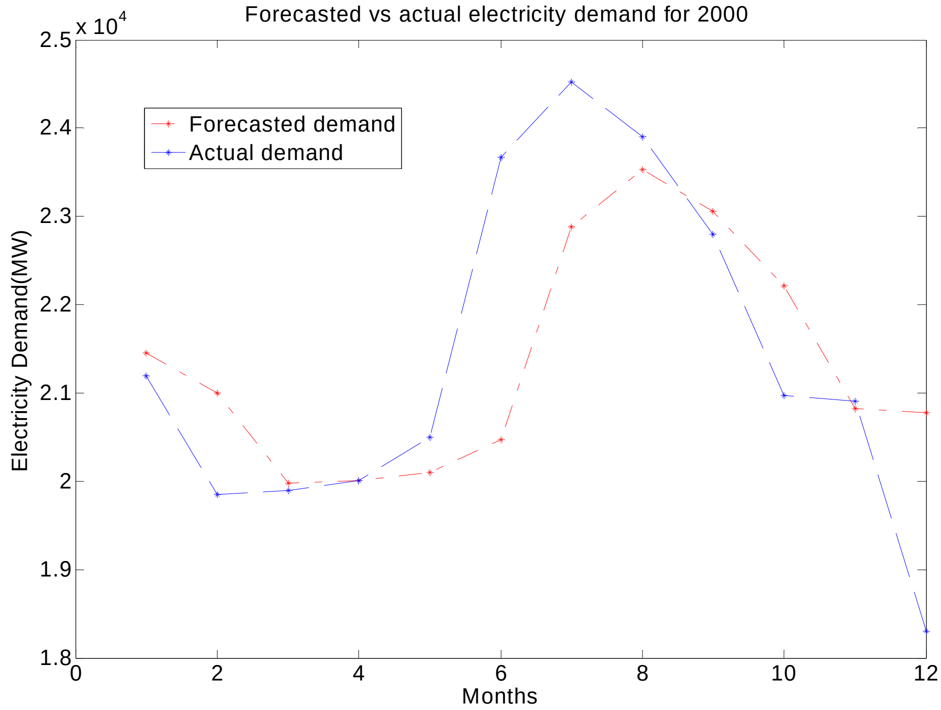

Figure 4.2. Forecasted Versus Actual Demand

Figure 4.3 shows the residual bar plot for the forecasted period. During the months of June and July, the forecasted demand is less by 3000MW and 1500MW, respectively. In December 2000, it is greater by 2400MW. The Root Mean Square Value gives the best estimate of the deviation between the forecasted and actual demand values for the entire duration. The forecast root mean square error factor, which gives an estimate of the accuracy of the forecasted value, is calculated as 1366.1 MW.

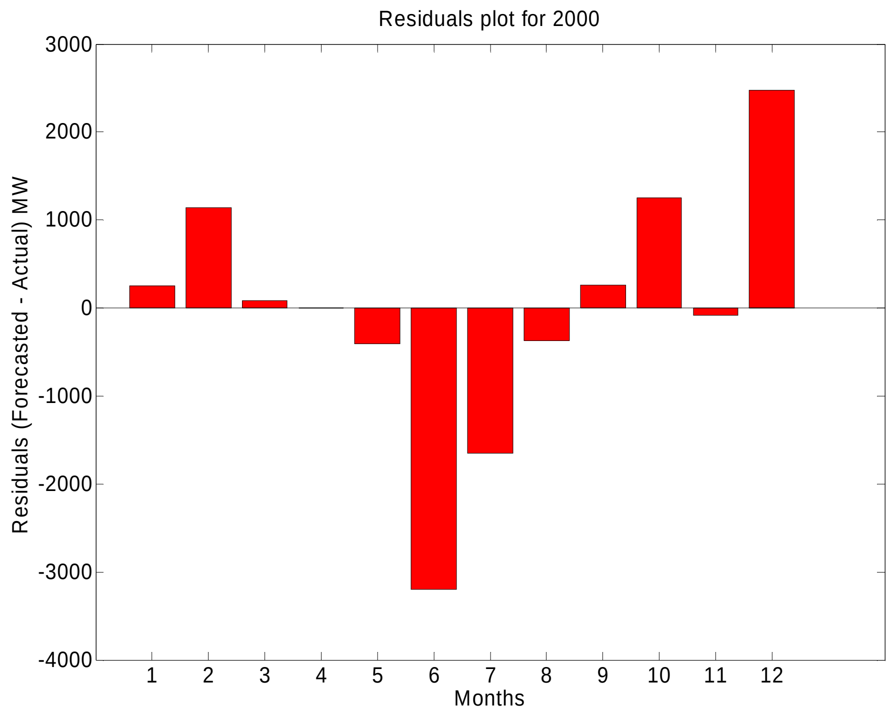

Figure 4.3. Residuals Distribution

The next section discusses the demand volatility forecasting using the GARCH (1, 1) model. The inputs to this model are the forecasted demand and the time period. The parameters estimated are the weights alpha, beta, gamma and variance rate. The output from this model is the estimate of the demand volatility.

5. FORECASTING VOLATILITY IN THE ELECTRICITY DEMAND

5.1. FORECASTING DEMAND VOLATILITIES

5.1.1. GARCH (1, 1) Model. In this section, an explanation is made as to how historical data can be used to produce estimates of current and future levels of volatilities. Estimating future volatilities is useful for the calculation of Value-at-Risk (VaR). Here, Generalized AutoRegressive Conditional Heteroscedasticity (GARCH) is used to model the future volatilities against Variance (Standard Deviation). The most important feature of this model is that the inconstant volatilities keep on changing day-by-day. Heteroskedasticity is defined as the variations in the volatility on a day-to-day basis. The phenomenon of heteroskedasticity is observed in the electricity demand data. The GARCH model is used because it explains the heteroskedasticity and attempts to keep track of the variations in volatility. In this model, the volatility value for a particular day is calculated using the value at the end of the previous day.

The key parameter of interest is to calculate the daily variance rate in demand using the previous day's data. ${\sigma_n}^2$ is the variance rate on day n and ${\sigma_{n-1}}^2$ is the variance at the end of day (n-1). Here, u_n is defined as the daily percentage change in the demand value.

$$u_n = \frac{S_n - S_{n-1}}{S_{n-1}} \tag{3}$$

The model used to estimate the variance is

$${\sigma_n}^2 = \gamma.V_L + \alpha.{u_{n-1}}^2 + \beta.{\sigma_{n-1}}^2 \tag{4}$$

The parameters $\alpha, \beta, \gamma, V_L$ are estimated from the historical data (January 1999 to September 2000). The values of α, β, γ are the weights assigned to ${u_{n-1}}^2, {\sigma_{n-1}}^2, V_L$ respectively. These weights must total to one. These weights determine the value of long-term mean variance and hence, the volatility.

By setting $\omega = \gamma.V_L$, Equation 4 can be written as

$$\sigma_n{}^2 = \omega + \alpha.u_{n-1}{}^2 + \beta.\sigma_{n-1}{}^2 \tag{5}$$

5.1.2. Methodology. The Maximum Likelihood Method is used to determine the parameters $\alpha, \beta, \gamma, V_L$ [1]. It is a popular statistical method used to calculate the best way of fitting a mathematical model to the data. Modeling real world data by estimating maximum likelihood offers a way of tuning the free parameters (weights) of the model to provide an optimum fit. Let $\sigma_n{}^2 = V_n$. The best estimate of V_n is that value which maximizes the following function:

$$f_n = \sum_{i=1}^{m} [-\ln(V_n) - \frac{u_n{}^2}{V_n}] \tag{6}$$

For the first step, assume some temporary values for α, β, ω to determine the value of the function f_n and its sum. In the next step, regression analysis is used to estimate the true values of α, β, ω that maximize the sum obtained. The steps are explained in Appendix A. The Long-term variance rate is given by:

$$V_L = \frac{\omega}{1 - \alpha - \beta} \tag{7}$$

The Long-term volatility (Standard Deviation) = $\sqrt{V_L}$, therefore, $\omega = \gamma.V_L$ giving $\gamma = \omega / V_L$. After checking to see that $\alpha + \beta + \gamma = 1$, a graph of $\sqrt{\sigma_n{}^2}$ versus days, i.e., volatility or standard deviation versus days can be plotted. Using the estimated values of $\alpha, \beta, \gamma, V_L$, and using the previous day's data for u_{n-1} and σ_{n-1}, the variance, and hence, the volatility in demand for the next day can be calculated using Equation 4.

5.2. DATA AND NUMERICAL RESULTS OF STUDY

5.2.1. Data. The electricity data used for this study are publicly available. The University of California Energy Institute (UCEI) sponsored a collection of data related to the newly restructured electricity markets in California. Data from this collection was used, representing the day-ahead market clearing prices and quantities in the Power Exchange (PX). The dataset for this study is comprised of data from April 1998 to December 2000.

For the GARCH model, the demand data from January 1999 to September 2000 is used to estimate the values of the parameters $\alpha, \beta, \gamma, V_L$. The estimated values are used in Equation 4 to forecast the daily volatility in the demand for the period October 2000 to December 2000.

5.2.2. GARCH (1, 1) Model Results. The parameters used for the GARCH model appear in Table 5.1, given the sampling population (training data) used. Alpha (weight associated with previous demand) has a value 0.0201, Beta (the weight associated with variance rate) is 0.6572 and Gamma (weight for long-term variance rate) is 0.3227. Beta has the highest influence on Long-term volatility.

Table 5.1. GARCH Model Parameters

Alpha	**Beta**	**Gamma**	**Omega**	**Long-run Average Variance Rate**	**Long-run Average Volatility Rate**
0.0201	0.6572	0.3227	0.0016	0.0050	7.04%

Figure 5.1 shows the pattern by which the volatility of electricity demand changed over the 21 month period from January 1999 to September 2000. The volatility was higher during the summer months of June and July, which coincides with huge increase in the demand experienced during these months. The volatility changes on a daily basis and the phenomenon of heteroscedasticity is evident from the plot.

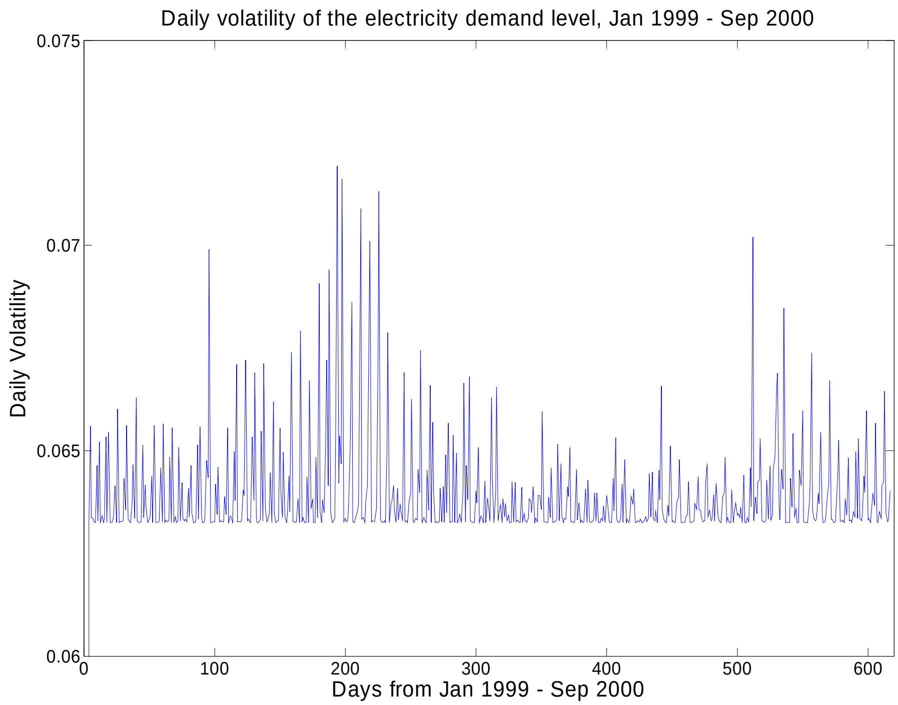

Figure 5.1. Volatility for the 21-Month Period

The parameters values from Table 5.1 are used to forecast the daily volatility in the electricity demand from October 2000 to December 2000. Figure 5.2 shows the forecasted daily volatility in the electricity demand over the 90 day period. During the first and second month the volatility was between 5% and 5.5%. During the third month the volatilities were higher, exceeding 6%. These values are considered high in the trading market which move up or down very quickly. Volatility values are used on different occasions. For instance, it is an important factor in the pricing of options since higher the volatility higher is the price of options on futures (premium) because the probability of the option attaining the intrinsic value or moving deeper 'in-the-money' increases. In this study, hedging strategies for financial risk reduction are formulated based on the forecasted demand and volatility values. Based on the volatility, it is possible to have an estimate of the deviation in the selling price of electricity in the future for different risky scenarios. The values of expert probabilities used in section 6 are based on the historical volatility value in the electricity demand.

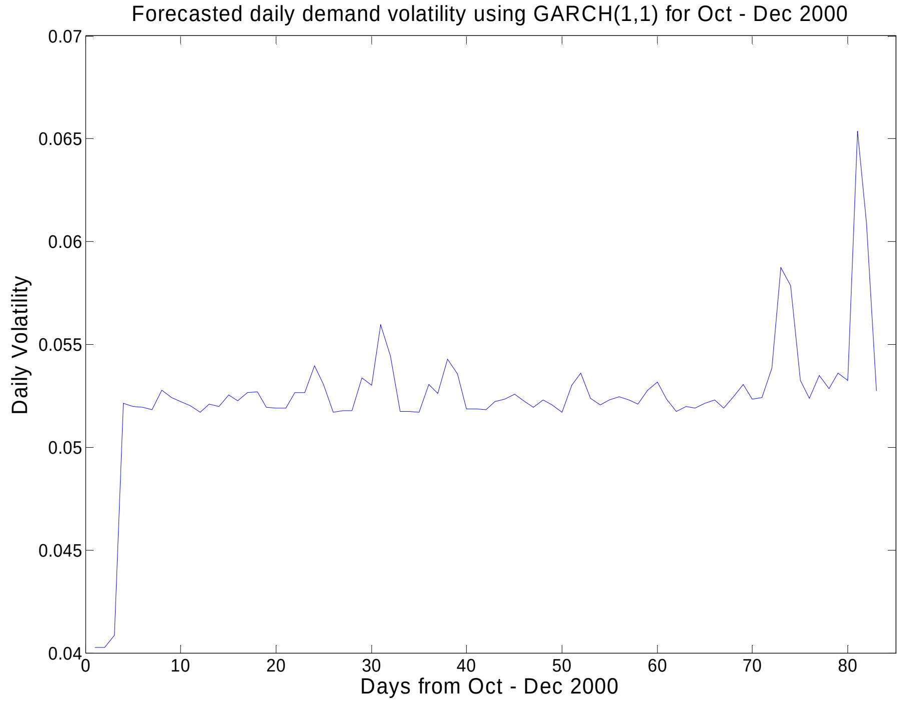

Figure 5.2. Forecasted 90-Day Period Volatility

The next section discusses the hedging strategies for financial risk mitigation. The inputs to this model are the forecast of electricity demand and volatility. The effectiveness of the hedge is measured in terms of Revenue to Loss ratio and the Net wealth change parameters. The results of this model indicate the stabilization of the expected profit margin as a result of hedging.

6. HEDGING STRATEGIES FOR FINANCIAL RISK MITIGATION

6.1. RISK MITIGATION

Risk analysis is the process of identifying, quantifying and handling the occurrence of an undesirable event in the future, which in this case is the targeted selling price risk. One approach is to use derivatives of energy commodities as financial instruments to hedge the exposure to price risk. Contractual agreements for a wide range of energy commodities are traded in the New York Mercantile Exchange. Agreements that include futures give the owner the obligation and options give the right but not the obligation to buy or sell the underlying primitive commodity for a certain price at a certain time in the future.

6.1.1. Risk Mitigation Framework. A cross-hedge is performed by hedging the cash price of one commodity with the futures price of another commodity. For performing the cross-hedge, both of the commodities should have a correlation between each other. In this study, the spot electricity price risk is hedged using the natural gas futures contract. The correlation between electricity and natural gas price is positive, implying that both the prices move in the same direction. An increase in the price of natural gas tends to increase the price of electricity for gas-fired electricity generators. The steps necessary for carrying out the risk reduction functionality are shown in the framework in Figure 6.1.

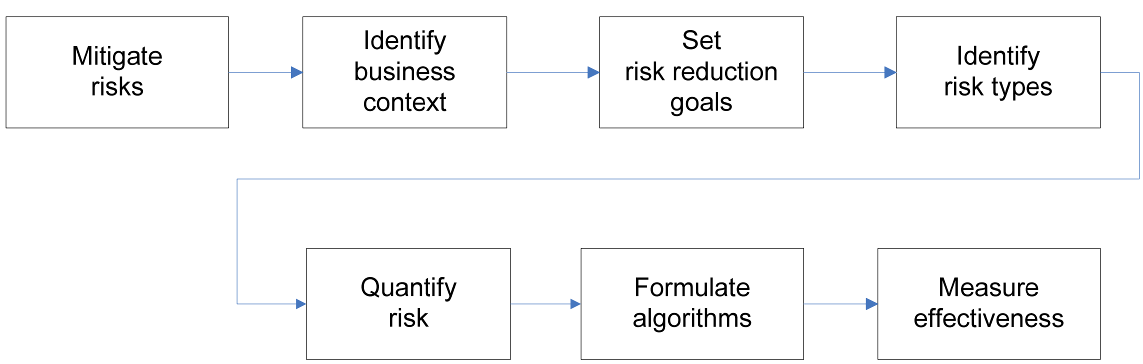

Figure 6.1. Risk Mitigation Framework

6.1.2. Case Study – Risk Mitigation by Hedging. The main objective of this case study is to implement the proposed risk mitigation framework within a real-world example. The study is performed on the publicly available electricity data from the California Power Exchange and the natural gas futures data from NYMEX. The dataset for this study is comprised of data from January 1999 to December 2000.

The business context is the risk faced by the electricity generator company, which expects to supply some specific quantity of power at time t+1, for a price pre-determined at time t. Since the futures contracts have month-ahead delivery dates, a lead time of one month is considered. For instance, if time t represents 01-January-1999, then time t+1 correspond to February-1999. The risk reduction goal is to stabilize the profit margin for different risky scenarios. The risk considered here is the financial risk. Risk can also be stated as the probability that the outcome might result in a loss, which leads to uncertainty. If the risk leads to financial loss, it can be termed a financial risk. This type of risk results in a decrease in revenues and hence, the operating profits.

6.1.2.1 Quantify risk. The term quantitative risk analysis generally implies the reliance on probability and statistics. However, few quantitative risk analysis methodologies, such as maximin, minimax and game theory do not depend on probability. This study builds on the existence of probabilities for determining the outcomes. Probabilities based on historical data and systemic observations are called 'objective probabilities'. Since it is not possible to obtain historical data, the probabilities based on expert evidence, referred to as 'subjective probabilities', are used here.

Two methods are available in the literature for generating expert evidence based probabilities – the fractile method and the triangular distribution method [25]. The fractile method requires the expert to asses the probabilities of different outcomes. The expert should be comfortable with probabilities. The triangular distribution follows a similar approach to the one used in the fractile method. However, only three assessments are required – Optimistic, Pessimistic and Most-Likely estimates of the outcomes. This approach is less complex, aids in fast calculation, and is easy to simulate.

A simple triangular distribution, which is shown in Figure 6.2, is a reasonable Probability Density Function (PDF) for describing the risk. Its structure is based on three parameters: the 'minimum' selling price (pessimistic), the maximum selling price (optimistic) and the 'most likely' selling price.

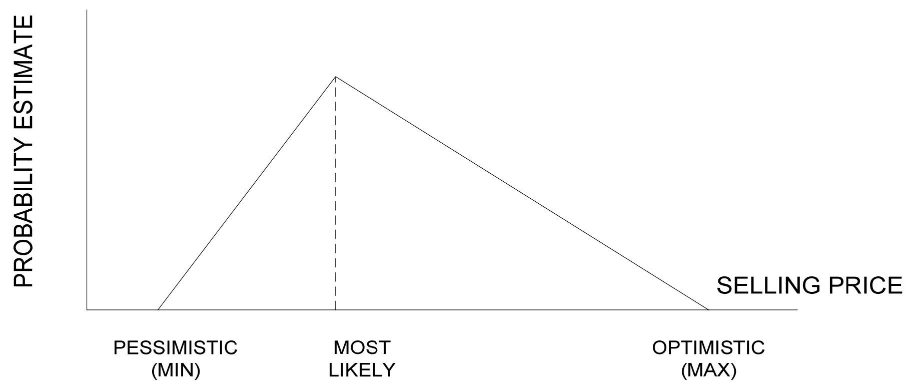

Figure 6.2. Triangular Probability Distribution

Table 6.1 relates the risk values of low, moderate, high, and very high to a set of risk factor multipliers. It has been developed by experts to facilitate risk estimation [26]. The 'risk factor multipliers' in the table provide a reasonable range of risk quantification for the problem considered here.

Table 6.1. Risk Factor Multipliers

		Price ($) per MW		
Code		**Min**	**Most Likely**	**Max**
Low risk	L	0.96	1	1.05
Moderate risk	M	0.91	1	1.16
High risk	H	0.83	1	1.29
Very High risk	V	0.68	1	1.57

Interpretation of Table 6.1 shows that for a scenario coded 'Low risk', the 'min' is defined as 4% less than the 'most likely' and the 'max' is defined as 5% more than the 'most likely'. Suppose on 01-January-1999 that the generator company decides to sell 1515 MW of electricity on February-1999. The company targets a price of $25 per MW, or a total selling price of (25)*(1515) = $37,875. If the price falls below $25/MW, it will result in a decrease in the revenues. The risk in this case is the 'Selling Price'. The 'most likely' value is $25/MW. Table 6.2 shows the quantification of the three parameter values for each of the four risk codes.

Table 6.2. Price at Different Risk Codes

		Price ($) per MW		
Code		**Min**	**Most Likely**	**Max**
Low risk	L	24	25	26.25
Moderate risk	M	22.75	25	29
High risk	H	20.75	25	32.25
Very High risk	V	17	25	39.25

6.1.2.2 Formulate algorithm. The formulation of hedging strategies is performed as a six-step process, using the available dataset. As a first step, the electricity generator company sets the target selling price (i.e. the price per MW) for the electricity to be delivered in the future. If the actual price happens to be less than the targeted price, the company will realize a decrease in the operating profit. Therefore, it is necessary to model the risk involved in dollar terms (risk quantification).

Whenever there is randomness about future, probability is used to model the uncertainty, such that the price risk is modeled as a Probability Distribution Function. This is the second step. Expert opinion based studies for understanding the future states of economy are widely used in risk analysis. As a third step, the risk factor multipliers based on expert opinion are obtained. The values are shown in Table 6.1. Using these multiplier values, the price risk in dollar terms is calculated as the fourth step. Based on the values obtained, cross-hedging strategies involving a natural gas futures contract are formulated, simulated, and the results verified. These final two steps are used to formulate algorithm functionality. The six steps are shown in Figure 6.3.

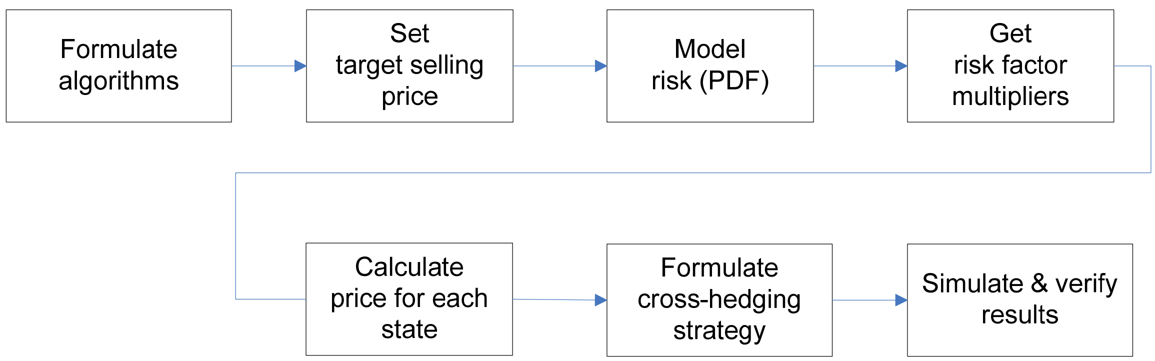

Figure 6.3. Formulate Algorithm Function

The next section describes the two cross-hedging strategies: one as a financial hedge and the other as a physical hedge.

6.1.2.3 Financial hedge – no physical delivery of the asset. Suppose that on 01-January-1999 the generator company anticipates selling electricity at $25 per MW. The natural gas futures price on this date for February-1999 delivery is $2.275 per mmBTU. For performing cross-hedge, the first step is to estimate the number of futures contracts needed. The quantity 'Optimal Hedge Ratio' indicates the number of futures contracts required for a unit risk. It refers to the number of futures contract for 1 MW of electricity that will be sold. The equation for calculating the optimal hedge ratio (h) is:

$$h = \frac{\operatorname{cov}(s, f)}{\sigma_f^{\ 2}} \tag{8}$$

where

σ_s	Standard deviation of electricity spot price over the hedging period
σ_f	Standard deviation of natural gas futures price over the hedging period
$\operatorname{cov}(s, f)$	Covariance between spot and futures price over the hedging period

If ρ represents the correlation between spot and futures price, Equation (1) can be rewritten as:

$$h = \frac{(\rho)(\sigma_s)(\sigma_f)}{\sigma_f^{\ 2}} = \rho\left(\frac{\sigma_s}{\sigma_f}\right) \tag{9}$$

From the real-time data, the optimal hedge ratio for January-1999 is calculated to be 2.4945. This means that if at time t the company anticipates to sell 1 MW of electricity at time t+1, it can hedge against price risk by selling 2.4945 MW worth of futures contract. Time t corresponds to 01-January-1999 and time t+1 correspond to February-1999. In cross hedging, both the units are not same since two different commodities are involved. The company performs two transactions: First, it sells 2.4945 MW worth of futures contract (short sale) on 01-January-1999 at $2.275 per mmBTU. These futures contracts are for delivery during the next month. The trading terminates on 26-January-1999, three business days prior to 01-February-1999. On 26-January-1999, the company closes its short sale by buying the same number of futures contracts in order to avoid physical delivery of natural gas.

The correlation coefficient between spot and futures price is calculated to be 0.7260. Therefore if the price of electricity decreases at time t+1, the price of natural gas futures also decreases. If the short-selling price at time t is high, the buying price at time t+1 is less. The difference in these two values, to some extent, reduces the loss in the targeted revenue for the generator company. If the optimal hedge ratio turns out to be negative, the company can buy the same amount of futures contracts. The transactions are shown in Table 6.3. For the correlation coefficient mentioned, if the electricity price decreases by $1 per MW, the natural gas futures price decreases from $2.275 to $2.165 per mmBTU.

Table 6.3. Cross-hedging Using Natural Gas Futures

	Cash Market	**Futures Market**
t = 0; 01-Jan-99	Plan to sell 1515MW at $25 per MW, which should net the firm 1515*25=$37,875	Sell 2.4945 MW worth of natural gas futures contract. Price is (6600*1000)*2.4945*1515 =24,962 mmBTU. Current futures price is $2.275 per mmBTU. Total futures price = 24,962 * 2.275 = $56,744
t = 1; 1 month	Sell electricity at $24 per MW, which will net the firm 1515*24 = $36,360	Buy the same number of futures contract to close out the short-sale position. Current futures price = $2.165 per mmBTU. Buy price = 24,962 * 2.165 = $54,043
	Loss = $1,515	Profit = $2,701
	Net Wealth Change = $1,186	
(0.7260 $ / 6.6 mmBTU) * 1 mmBTU = $0.11 per mmBTU (2.275 – 0.11 = $2.165)		

The same hedging strategy is followed to compute the net wealth change for all four risk codes. Results for the four risky scenarios are presented in Figure 6.4. This chart shows the two sets of bars for the four risky scenarios. The bars in blue show the loss that the company would have incurred if no hedging was carried out, and the ones in red show the profit made due to the hedge in place. The bars are arranged from low risk to very high risk from left to right. The purpose to carry out hedging is not to profit from it, but to reduce the downside potential. The cross hedging strategy is tested for four different risky scenarios and the dollar values are denoted by the bars in Figure 6.4. The target selling price varies depending on the risk of the future scenario. The values obtained using expert opinion based probabilities are used to formulate the strategies.

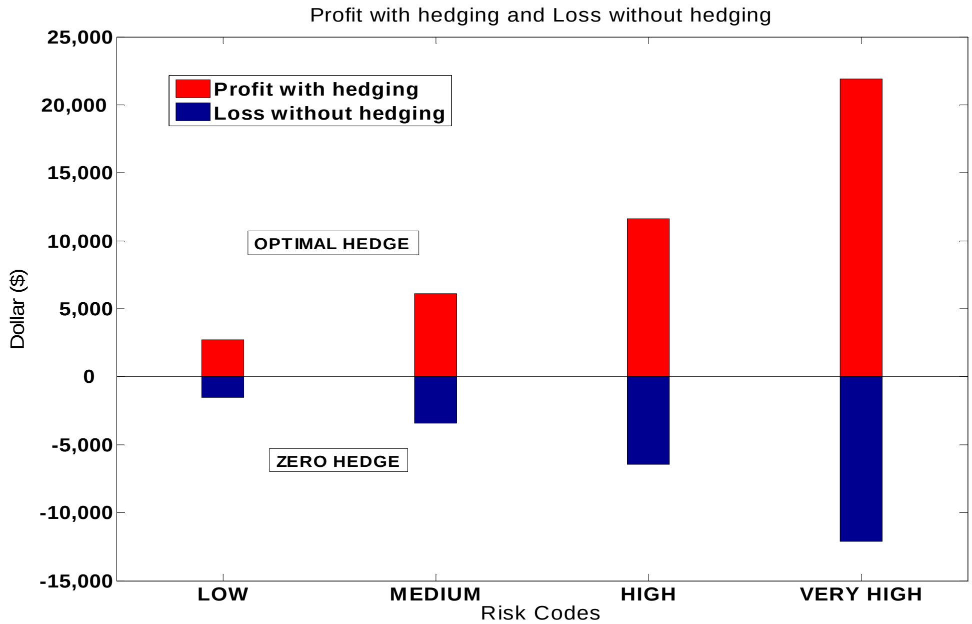

Figure 6.4. Profit and Loss for Different Risk Codes

"Zero Hedge" refers to no hedge at all. It has resulted in a loss for company since the expected target revenue is not achieved. "Optimal Hedge" has resulted in eliminating the loss and had contributed to a positive wealth change for the company.. The performance of the hedge is defined in terms of a Revenue To Loss (RTL) ratio. The RTL is a new parameter mentioned here, defined as the ratio of cash inflow due to hedging to the loss that would have occurred without hedging. It can be seen that the RTL ratio is approximately the same for the different scenarios. Hedging has resulted in stabilizing the profit margin, as indicated by the values in Table 6.4.

Table 6.4. RTL Ratios for Four Risky Scenarios

	Low Risk	**Medium Risk**	**High Risk**	**Very High Risk**
RTL Ratio	78.28%	79.93%	80.54%	80.87%

6.1.2.4 Physical hedge – physical delivery of the asset. So far, the case study has dealt with the case of hedging as a financial contract. Physical delivery of natural gas is advantageous for gas fired electricity generation plants in order to meet the surge in demand for electricity. For instance, on a very cold day, the demand for electricity might be higher that usual. In such situations, the company can procure natural gas from the nearest distribution center and use it for electricity generation. If the spot price is very high, the company is at a price risk. In order to avoid this exposure, the company can make use of a natural gas futures contract to lock into a fixed price by taking a long position, especially during the summer and winter months. Natural gas is transported from production fields to distribution centers. The most important market center in the US is the Henry Hub, located in Louisiana. It is the most active and highest-volume traded center. The NYMEX traded futures contracts use Henry Hub as the physical delivery point. From this hub, the gas is supplied to different distribution centers through pipelines [29]. The party with a short position in the futures contract is responsible for the physical delivery of natural gas.

Options are the other type of financial derivatives that can be used as risk mitigation instruments. Specifically, a spark spread option is a type of call option which can be used effectively to minimize the exposure to power price risk. It describes the payoff of the gas-fired electricity generation asset. The spark spread is the difference between the electricity price and the electricity generation cost. It is defined as:

Spark spread = Electricity Price – (Standard heat rate * Natural gas price) (10)

Fred [30] has modeled spark spread option using a mean reverting model and Fourier transforms. It was also used for the valuation of electricity generation assets as a real option [31]. Spark spread is a type of call option that provides the holder, the right, but not the obligation to buy or sell an asset at an agreed price at a specific time in future. If S_t is the spot price of the underlying asset and *K* is the strike price of the option expiring at time *T*, then the payoff of the call option is $Max[S_t - K, 0]$. The holder of the call option decides to exercise the option only if the spot price is greater than the strike price. Similarly, the owner of the gas-fired plant will decide to operate the plant only if the spot price of electricity is greater than the cost of generation of the unit. This is similar to a call option with a payoff given by:

$$Max[(P_e - (h * P_n)), 0] \tag{11}$$

where

P_e	The spot electricity price
P_n	The spot gas price
h	The standard heat rate

The hedging strategy adopted here is that the plant operator simultaneously enters into a short position in the electricity forward contract and a long position in the natural gas futures contract. Since both the markets have a positive correlation between them, a loss suffered in one market will be compensated by a gain in the other market. The magnitude of the profit or loss determines the overall result. The standard heat rate is 6600*1000 BTU per MW. The electricity forward contract obligates the operator to deliver power during the delivery month. The gas futures contract obligates the operator to accept delivery of natural gas during the delivery month. Both the contracts mature during the subsequent month. For instance, let us consider the following scenario observed on 01-November-2000. The plant owner hedges by entering into a short month-ahead COB[1] electricity forward contract for $100.6 per MW, and a long Contract-1 natural gas futures contract[2] for $4.618 per mmBTU. By doing so, the plant owner locks into a profit margin of [(100.6 – (4.618/0.1515)] = $70.12 for each MW of power. (Note: this calculation uses 0.1515 because at the given heat rate, 0.1515 MW of electricity will be generated from 1 mmBTU of natural gas).

For instance, on a particular day (say 01-December-2000), the spot electricity is $120 per MW and the spot natural gas price is $17 per mmBTU. The plant will be

---

[1] COB forward contracts are for 432 MWh each, to be delivered at the rate of 1 MW/hour for 27 days of a month. They are available for delivery during any of the 12 months.

[2] Contract-1 futures contract are for delivery during the next month. They are available for delivery during any of the 12 months. One contract is for 10,000 mmBTU of natural gas. Other contracts are named Contract-2, Contract-3 and Contract- 4 to represent contracts 2, 3 and 4 months out respectively.

operated and the profit margin is still $70.12. Without hedging, the profit margin would have dropped to [120 – (17 / 0.1515)] = $7.78.

As another instance, if the spot electricity on 01-December-2000 is $112 per MW and the spot natural gas price is $17 per mmBTU, the plant will not be operated in this case since the spot electricity price is less than the cost of operating the plant [Spark spread = 112 – (17*6.6) = -0.2112]. However, the owner has obligations on the futures contracts. For the short position, the owner buys electricity from the spot market at $112 per MW and delivers it. For the long position, the owner accepts deliver of natural gas at $4.618 per mmBTU and sells it in the spot market at $17 per mmBTU. The profit margin from doing so is [(-112 + 100.6) - (4.618/0.1515) + (17/0.1515)] = $70.33, where the negative sign indicates buying (cash outflow) and the positive sign indicates selling (cash inflow) for the owner. The different feasible scenarios are indicated in Table 6.5.

Table 6.5. Profit Margin With and Without Hedging

<table>
<tr><td></td><td colspan="5">At the time of hedging (entering into forward and future contracts):
Electricity forward price=$100.6/MW
Natural gas futures price = $4.618 / mmBTU
Profit margin locked upon = $70.12/MW</td></tr>
<tr><td></td><td></td><td></td><td></td><td colspan="2">Profit Margin</td></tr>
<tr><td>Scenario</td><td>Spot electricity price ($/MW)</td><td>Spot natural gas price ($/mmBTU)</td><td>Plant operation</td><td>With Hedging ($/MW)</td><td><b>Without Hedging ($/MW)</td></tr>
<tr><td>1</td><td>110.6</td><td>5.186</td><td>Yes</td><td>70.12</td><td>76.37</td></tr>
<tr><td>2</td><td>100.6</td><td>3.5</td><td>Yes</td><td>70.12</td><td>77.5</td></tr>
<tr><td>3</td><td>100.6</td><td>6</td><td>Yes</td><td>70.12</td><td>60.99</td></tr>
<tr><td>4</td><td>80</td><td>2</td><td>Yes</td><td>70.12</td><td>66.79</td></tr>
<tr><td>5</td><td>120</td><td>17</td><td>Yes</td><td>70.12</td><td>7.78</td></tr>
<tr><td>6</td><td>112</td><td>17</td><td>No</td><td>70.33</td><td>-0.2112</td></tr>
</table>

For scenarios 3 to 6, hedging turned out to be advantageous because the profit margin would have decreased if a hedge is not put in place. For instance, in scenario 4, when both the electricity and natural gas spot prices fell, the hedge had guaranteed the anticipated profit margin. For the scenarios 1 and 2, hedging turned out to be disadvantageous because it has circumvented the favorable price movements. For all the scenarios, hedging has resulted in stabilization of the profit margin.

The plot in Figure 6.5 compares the variation in the profit margin with and without hedging for different scenarios. When no hedge is put in place, the profit margin fluctuates between $0 and $77.50. This variation is avoided by hedging using futures contracts. Hedging, while reducing the loss due to unfavorable market movements, also eliminates the potential to gain from favorable market movements.

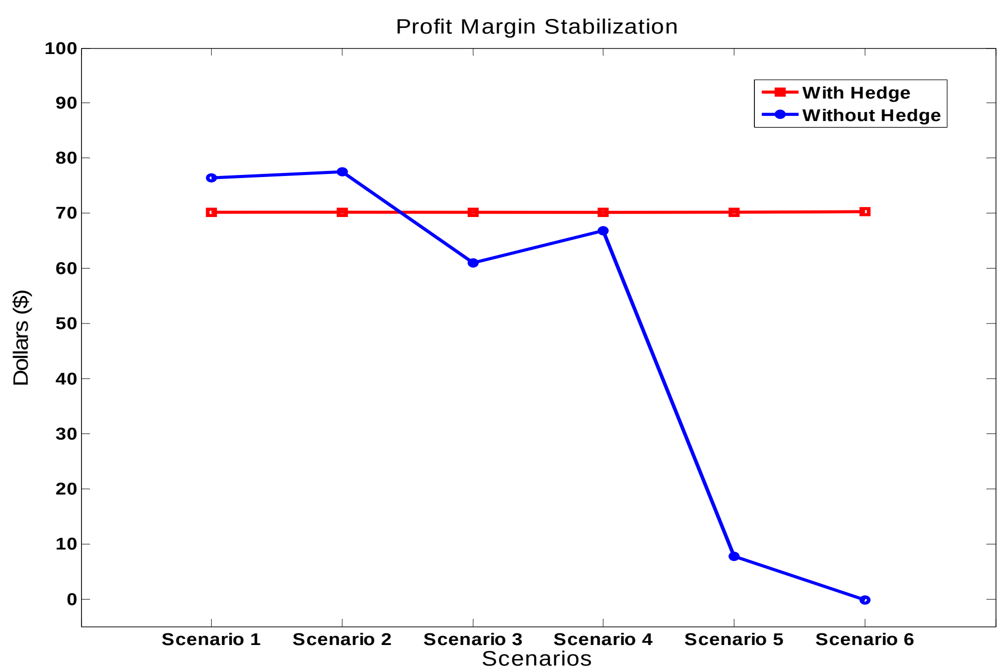

Figure 6.5. Stabilization of Profit Margin

6.2. DISCUSSION

The case study emphasized on two hedging strategies using futures contracts from different commodity markets. Eva Tanlapco et al. [9] in their paper say that direct hedging is superior to using a cross-hedging strategy in the electricity industry. Although this might be true theoretically, direct hedging might not be always feasible. In actual hedging applications, the nature of hedging is determined by several factors, such as the time span covered and liquidity for that commodity markets, among others. For instance, let us consider a plant operator who enters into a short financial hedge position using electricity futures contracts. This market has lesser trading than the natural gas futures market. When the operator plans to close out the position just before the expiry date, it might be difficult because there are no contracts to buy. If the operator is unable to close the position before the delivery month, the responsibility for physical delivery lies with the operator. This gives rise to an additional risk. Illiquid markets usually pose such risks. The natural gas futures market is comparatively more liquid than electricity futures market. A press release from NYMEX stated that in 1999, the volume of natural gas futures contracts traded was 15,978,286, versus 128,423 contracts for California Oregon Border (COB) electricity futures [33].

The scope of this research is limited to the two types of hedging strategies discussed. It would be interesting to compare other hedging strategies to the ones discussed in this work. Other types of hedging include dynamic hedging, a multiperiod hedging approach, and a replicating portfolio approach. The choice of the hedging strategy depends on the circumstances and the risk aversion rating of the company. Risk is directly proportional to the return and so a company interested in higher returns might prefer not to formulate risk reduction hedging strategies in place.

The next section states the results of the mean reversion model and the GARCH model. The forecast mean square error is used to estimate the accuracy of the forecast made using the mean reversion model. The two hedging strategies proposed are compared to determine which of these is advantageous for the electricity generator company depending on the circumstances and the availability of suitable data. The scope for further research and investigation using the models used in this research are also discussed in the next section.

7. CONCLUSION AND FUTURE RESEARCH

7.1. CONCLUSION

This work discusses the risk management for the existing U.S. electricity generation system. The problem faced by the electricity generator companies and the modeling approach to this problem are described. The mean reversion model for forecasting long-term demand is proposed. Electricity demand has a strong deterministic component due to seasonal effects. The monthly average demand level and the speed of reversion for each month are estimated. While one year training data (monthly values) is insufficient to provide an accurate forecast, it is reasonably good to provide a starting point for understanding the effect of seasonality on electricity demand. The monthly electricity demand forecasted using mean reversion model is close to the actual demand, with the forecast root mean square error of 1366.1 MW. The error can further be reduced by employing the same procedure on a larger dataset, if available, for training purpose. Daily and hourly seasonal patterns have a high influence in the demand on a daily basis.

Since the electricity demand has a strong heteroscedastic behavior due to seasonal effects, a GARCH model for forecasting demand volatility is proposed. This model forecasts the daily volatility rate and the trend, along with the long-run variance rate. The daily demand volatility of 5.5%, forecasted using the statistical GARCH model indicates that the demand is high in volatility.

A risk mitigation framework for reducing the exposure to electricity price risk is proposed. A case study describing the implementation of the steps mentioned in the framework is undertaken. The risk is quantified using a triangular probability distribution function for different risky scenarios. Two cross-hedging strategies, one as a financial hedge and the other as a physical hedge are formulated and simulated for different scenarios. The results of the simulated scenarios indicate the performance of the hedge. For a financial hedge, the results of the simulation with and without hedging are compared in terms of "Net wealth change" and "Revenue To Loss" ratio. For a physical hedge, the results illustrate the stabilization of the anticipated profit margin as a consequence of hedging. Both the advantages and disadvantages of hedging are discussed based on the results.

7.2. DISCUSSION

In cross-hedging it is hardly possible to have a perfect hedge - a hedge leaving total wealth unchanged [32]. Table 7.1 shows the comparison between the two hedging strategies.

Table 7.1. Comparison of the Two Hedging Strategies

Scenario	**No Physical Delivery Strategy**	**Physical Delivery Strategy**
1	The plant operator acts as an "Outright position trader", who speculates the future price movements and takes a position.	The plant operator acts as a "pure hedger", who profits in one position and loses in the other position, depending on the price movements.
2	Best suited when the liquidity is very high in the futures market.	Best suited when the spot natural gas price drives the electricity sale price for the operator.
3	It is useful when the plant operator has no storage facility.	It is useful when the plant operator has a storage facility.
4	It is advantageous when the operator is located far away from the gas distribution center.	It is advantageous when the operator has ready access to a nearby gas distribution center.
5	In situations when transportation costs are very high.	In situations when the transportation costs are not high.
6	The plant operator anticipates spot and futures commodity price movement is in the same direction.	The plant operator anticipates random (non-linear) price movement between the spot and futures commodities.

The intention for carrying out hedging is not to profit from it, but to reduce the loss. With this approach, the electricity generator company can adopt any of these two hedging strategies depending on the circumstances. While there are many different types of hedging strategies involving futures and options, it is impossible to generalize which of these strategies is the best. It depends on every firm's individual characteristics, hedging objectives and risk aversion.

7.3. FUTURE RESEARCH

The single factor mean reversion model can be extended to two-factor mean reversion model, by incorporating temperature as one of the parameters in the model. The bidding behavior of the electricity traders can be simulated using an agent based modeling approach. This approach requires a group of people to simulate the market participant’s behavior under various scenarios. As the electricity market becomes more liquid, this would theoretically allow traders to form a replicating portfolio for electricity using oil and gas contracts. The replicating portfolio approach is widely used in financial engineering and financial markets for option pricing and binomial tree approaches. The effect of storing electricity in the secondary forms such as hydro-electric dams and back-up power stations can be studied depending on the availability of company specific data for this approach.

APPENDIX

MAXIMIZATION FUNCTION

Derivation for the value of V_n that maximizes the sum of the function in Equation 6.

$$\frac{d}{dV_n}(f_n) = \frac{d}{dV_n}[-\ln(V_n) - \frac{u_n^{\ 2}}{V_n}] = 0$$

Implies $$\frac{-1}{V_n} + \frac{u_n^{\ 2}}{V_n^{\ 2}} = 0$$

Implies $$\frac{-V_n + u_n^{\ 2}}{V_n^{\ 2}} = 0$$

$$V_n = u_n^{\ 2} \qquad (12)$$

Equation 5 can be rewritten as $u_n^{\ 2} = \omega + \alpha . u_{n-1}^{\ 2} + \beta \sigma_{n-1}^{\ 2}$

The values for $u_n, u_{n-1}, \sigma_{n-1}$ are available. Regression analysis is used to estimate the values of the coefficients α, β, ω.

BIBLIOGRAPHY

[1] John. C. Hull, "Introduction to Futures, Options and Other Derivatives," Sixth Edition, Prentice-Hall Inc, 2006.

[2] Energy Information Administration, 12-Sep-2007, "Official Energy Statistics from the US Government," Electricity Supply and Demand Fact Sheet, http://www.eia.doe.gov/cneaf/electricity/page/fact_sheets/supply&demand.html

[3] Edison Electric Institute, "Industry Overview and Statistics," 12-Sep-2007, http://www.eei.org/industry_issues/industry_overview_and_statistics.

[4] Jean-Thomas Bernard and Denis Bolduc and Donald Belanger, "Quebec Residential Electricity Demand: A Microeconometric Approach," *Canadian Journal of Economics*, Canadian Economics Association, vol. 29(1), pp. 92-113, 1996.

[5] J. Boland and L. Magnano (Australia), "Modeling Weekday Half Hourly Electricity Demand," From Proceeding (469) *Applied Simulation and Modeling*, ACTA Press, 2005.

[6] Ni Xiao a, Jay Zarnikau, Paul Damien, "Testing Functional Forms in Energy Modeling: An Application of the Bayesian Approach to U.S. Electricity Demand," *Energy Economics* 29, pp. 158–166, 2007.

[7] Ferda Halicioglu, "Residential Electricity Demand Dynamics in Turkey," *Energy Economics* 29, pp. 199–210, 2007.

[8] Julian Moral Carcedoa.T and Jose Vicens Oterob, "Modeling the Non-Linear Response of Spanish Electricity Demand to Temperature Variations," *Energy Economics* 27, pp. 477– 494, 2005.

[9] Petter L. Skantze and Marija D. Ilic, "Valuation Hedging and Speculation in Competitive Electricity Markets – A Fundamental Approach," Kluwer's Power Electronics and Power Systems Series, 2001.

[10] Carlos Blanco and David Soronow, "Mean Reverting Processes – Energy Price Processes Used For Derivatives Pricing & Risk Management," Financial Engineering Association, *Energy Pricing - Commodities Now*, 2001.

[11] Patrick E. McSharry, Sonja Bouwman, and Gabriël Bloemhof, "Probabilistic Forecasts of the Magnitude and Timing of Peak Electricity Demand," *IEEE Transactions on Power Systems*, 2005.

[12] Eva Gonzalez Romera, Miguel Angel Jaramillo Moran, Diego Carmona Fernandez, "Electric Energy Demand Forecasting with Neural Networks," University of Extremadura, 06071 Badajoz, Spain, *IEEE Transactions on Power Systems*, pp. 1860-1865, 2002.

[13] "Systems Engineering Fundamentals," *The Defense Systems Management College Press*, Fort Belvoir, Virginia, 2001.

[14] David L. Lindblad, "Systems Engineering: A Risk Management Approach," TRW Systems, ICBM Prime Integration Contract, *Technology Review Journal*, Fall/Winter 2001.

[15] Mugurel T. Ionita1, Pierre America2, Dieter K. Hammer1, Henk Obbink2 & Jos J. M. Trienekens1, "A Scenario-Driven Approach for Value, Risk, and Cost Analysis in System Architecting for Innovation," *Proceedings of the Fourth Working IEEE/IFIP Conference on Software Architecture*, WICSA 2004.

[16] S.J. Denga, and S.S. Orenb, "Electricity derivatives and risk management," Energy 31, pp. 940–953, 2006.

[17] R. J. Kaye, H. R. Outhred, and C. H. Bannister, "Forward contracts for the operation of an electricity industry under spot pricing," *IEEE Trans. Power System*., vol. 5, February 1990.

[18] T. W. Gedra, "Optional forward contracts for electric power markets," in *IEEE/PES Winter Meeting*, 1994.

[19] D. W. Lane, C. W. Richter, Jr., and G. B. Sheble, "Modeling and evaluating electricity options markets with intelligent agents," in *Proc. DRP Int. Conference*. Electric Utility Deregulation and Restructuring and Powering Technologies, 2000.

[20] C. J. Andrews, "Evaluating risk management strategies in resource planning," *IEEE Transactions on Power Systems*, vol. 10, Feb. 1995.

[21] Eva Tanlapco, Jacques Lawarrée, and Chen-Ching Liu, "Hedging With Futures Contracts in a Deregulated Electricity Industry," *IEEE Transactions on Power Systems*, Vol 17, No. 3, August 2002.

[22] Eric C. Honour, "Connecting an Architecture with its Emergent Properties," *Proceedings CSER 2007,* March 14-16, Hoboken, NJ, USA, 2007.

[23] Project Management Body of Knowledge. Upper Darby, PA: Project Management Institute, 1994.

[24] Aaron J. Shenhar, “From Theory to Practice: Toward a Typology of Project-Management Styles,” *IEEE Transactions on Engineering Management*, Vol. 45, No. 1, February 1998.

[25] John. C. Hull, “Introduction to Futures, Options and Other Derivatives,” Sixth Edition, Prentice-Hall Inc, 2006.

[26] Fred Raymond, “Quantify Risk to Manage Cost and Schedule,” *Journal of Acquisition Review* Quarterly – spring 1999.

[27] Energy Information Administration, 22-Oct-2007, “Derivatives and Risk Management in the Petroleum, Natural Gas and Electricity Industries,” http://www.eia.doe.gov/oiaf/servicerpt/derivative/chapter3.html.

[28] New York Mercantile Exchange, 22-Oct-2007, “Natural Gas Description,” http://www.nymex.com/ng_fut_descri.aspx.

[29] Charles Augustine, Bob Broxson, Steven Peterson, “Understanding Natural Gas Markets,” A Policy Analysis Study by Lexecon, an FTI Company, 2006.

[30] Fred Espen Benth and Jurate Saltyte Benth, “Analytical Approximation For the Price Dynamics of Spark Spread Options,” Dept. of Math, Pure Mathematics, Univ. of Oslo, No. 17, ISSN 0806-2439, August 2005.

[31] Shijie Deng, Blake Johnsony, Aram Sogomonianz, “Spark Spread Options and the Valuation of Electricity Generation Assets,” Proceedings of the 32nd Hawaii *International Conference on System Sciences*, 0-7695-0001-3/99, IEEE, 1999.

[32] Robert W. Kolb, “Futures, Options and Swaps,” Blackwell Publishing, Fourth Edition, 2003.

[33] New York Mercantile Exchange, 25-Oct-2007, “New York Mercantile Exchange Records Highest-Ever Annual Volume,” Press Releases http://nymex.mediaroom.com/index.php?s=43&item=1323.

VITA

Karthik Viswanathan was born in the town of Tirunelveli in the state of Tamil Nadu, India, on July 10, 1980. He graduated from Chinmaya Vidhyalaya Higher Secondary School in May 1997. The following August he entered Bharathiyar University in the city of Coimbatore, Tamil Nadu, India, and in May 2001 he received the degree Bachelor of Engineering (B.E.) in Electronics and Communication Engineering. He entered University of Missouri - Rolla in August 2006 and graduated with a master’s degree in Systems Engineering in May 2008, in the Department of Engineering Management and Systems Engineering.