Summer 2008

Speculation and hedging with virtuals

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SPECULATION AND HEDGING WITH VIRTUALS

by

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A DISSERTATION

Presented to the Faculty of the Graduate School of the

MISSOURI UNIVERSITY OF SCIENCE & TECHNOLOGY

In Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY
in
ENGINEERING MANAGEMENT

2008

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ABSTRACT

"Virtual bid" and "Virtual offer" are purely financial products offered in certain electricity markets. Theoretically, virtual bids and offers can change the electricity price as the bids and offers are stacked along with the demand and supply, respectively. This dissertation discusses how virtuals can be used to hedge and speculate in the electricity market.

A statistical simulation model is developed based on the day-ahead (DA) demand and real time (RT) load data from Midwest Independent Transmission System Operator's (MISO) footprint and DA and RT price observed at Cinergy hub. The simulation models are intended to mimic the load and price processes, taking the cyclical and correlation patterns in the market data into account as well as to provide a mechanism to incorporate stochastic variations that impact the processes. This model can then be utilized to study how the various trading strategies perform under deferent scenarios and thus provide better decision making tools to a trader. The DA Demand and RT Load are simulated using a combination of unobserved component models (UCM) and a set of regression variables. The DA Price and RT Price processes are replicated with GARCH based regression models. The regressor variables include principal components of different weather variables to capture the weather variation across MISO footprint and a set of dummy variables to model key patterns observed in the electricity market. The simulation models are used to generate test data sets which are then used to analyze different strategies involving virtuals. The simulation models also help to understand the relationship between DA and RT clearing prices. This research finds no evidence of DA/RT price convergence purely based on the virtuals trading at MISO. Based on the simulation results, the virtual bids appear to be most profitable during summer and winter and virtual offers appears to be most successful during shoulder months.

ACKNOWLEDGMENTS

I sincerely thank Dr. V. Samaranayake for his guidance, understanding, and patience. I highly appreciate Dr. Samaranayake for spending many of his weekends and evenings during the last one year discussing my research works. I would also like to thank Dr. David Enke for guiding me during my doctoral studies at Rolla. He encouraged me to take up research work in the areas of my own interest. My sincere gratitude goes to Dr. Zhen Liu for his willingness to advise me when he joined Rolla. I am also thankful to Dr. Grasman and Dr. Bohner for advising me on my dissertation work.

I would like to thank the Engineering Management and Systems Engineering Department (EMSE) at Missouri University of Science and Technology for supporting me during my graduate studies. I am also thankful to the faculty members and the administrative staffs at EMSE and the Mathematics/Statistics Department. In particular, I would like to thank Dr. Allada, Dr. Dow, Dr. Drain and Mrs. Krista Chambers for assisting me in many ways. I sincerely appreciate Mrs. Vicki Hudgins at the Office of Graduate Studies for her gracious help. I must thank my colleague, Mr. Asitha Edirisinghe, for his help in SAS programming.

Finally, and most importantly, I would like to thank my wife, Swarnali. I am thankful for her support, patience, outbursts, and unwavering love. I thank my parents, Pratima and Anil Shil for their encouragement and love and all the sacrifices they made for me. I am as ambitious as I am today because of my parents.

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1. INTRODUCTION

"Virtual bid" and "Virtual offer" are purely financial products offered in certain electrical markets. Market participants 'virtually' bid to buy or offer to sell electricity in the Day-Ahead Market (DAM). Therefore the instruments are termed as virtual bids and offers, respectively. The virtuals are created to allow the market participants to hedge their positions or speculate based on their understanding of the price divergence between Day Ahead and Real Time. The clearing house clears the virtual bids or offers based on the bid and offer price. However, the cleared virtuals are bought or sold at the Locational Marginal Price (LMP) observed at the Pricing Node or hub where the bid or offer was made. The cleared virtual bid and offers are stacked along with demand and supply to determine the market clearing price of electricity and therefore, theoretically, the increment in virtual bids and offers can move price. While the virtuals can be used for hedging different types of electricity market risks, a market maker can manipulate the price by using its bid and offer strategies (Isemonger and Rahimi, 2006; Saravia 2003).

In the recent past, there have been many scholarly publications studying electricity market and its elements (Bartels and Fiebig, 2000; Wen and David, 2001; Shawky and Barrett 2003; Isabel and Soares, 2005; Cuaresmaa et al., 2004; Harris 2006; Isemonger and Rahimi, 2006; Hadsell and Shawky, 2006). However, publications related to the virtual trading strategy and its effectiveness are very limited. This dissertation discusses how virtuals can be used to hedge and speculate in electricity market. We also show certain cases where one can manipulate the market situation with its bidding strategies and make arbitrage profits using virtuals. Also, most of the published literature in electricity market refer to the New York Independent Transmission Systems Operators (NYISO) or Pennsylvania-New Jersey-Maryland Interconnection (PJM) or California Independent Transmission Systems Operators (CAISO) (Duffie, Gray and Hoang, 1999; Saravia 2003). The focus of this research is the Midwest Independent Transmission Systems Operators or MISO, which is relatively new market and therefore did not find enough presence in the literature.

The simulation models presented in this dissertation are intended to mimic the load and price processes, taking the cyclical and correlation patterns in the market data into account as well as provide a mechanism to incorporate stochastic variations that impact the processes. This model can then be utilized to study how the various hedging strategies perform under different scenarios and thus provide better decision making tool to the trader. A combination of unobserved component models (UCM) and a set of regression variables are used to simulate the DA Demand (DAD) and RT Load (RTL). The DA/RT price processes are modeled using regression equations with GARCH errors. The regression variables include principal components of different weather variables to capture the weather variation across MISO footprint and a set of dummy variables indicating calendar effects in electricity market. Test data set is generated using the simulation models. These test data sets are used to analyze different trading scenarios involving virtuals. These simulation models also help to understand what could be DA and RT clearing prices. Understanding load and price processes would help the trader to make a decision on what price he or she should bid in or offer for In DA market.

In the following section, a brief description about some important features of the electricity markets have been discussed (Section 2). Literature related to the load modeling is discussed in Section 3 and literature related to price modeling is discussed in Section 4. Section 5 discusses two main risks involved in electricity market and hedging and speculative strategies using virtuals. Introduction to the unobserved component model (UCM) and GARCH models are given in Section 6. Preliminary data analysis and simulation modeling are discussed in Section 7. Finally, Section 8 discusses how to simulate the fitted model, trade analysis and inferences about the simulation results. For better readability, some of the figures and tables are included in the main text. Rest of the figures and tables are included in appendices.

2. ELECTRICITY MARKET

An electricity market provides a system and a mechanism to purchase and sell, or in other words trade electricity and electricity related physical and financial products. The price for electric energy is largely set by the supply and demand for it. The economics and the mechanics of the electricity market are quite different from those of a traditional commodity markets such as natural gas, corn or gold. The fundamental difference between the electricity market and other traditional commodity markets is that the underlying product, namely electric energy, cannot be stored.

Electricity price also depends on other variables such as weather, unit outage, transmission properties of electricity such as congestion, energy price, customer behavior and economy in general. The unpredictable and volatile nature of such variables creates higher risk for the generation and marketing companies. As a result, demand for financial products that could help the electricity generators and marketers hedge their risk against any possible financial losses have grown tremendously. This dissertation discusses how one such financial product, namely virtuals offered in organized markets such as PJM or MISO, can help the generators and marketers swing their risks based on their forecast and analysis. The product also creates opportunities for the speculators to make speculative trade profit. The most important aspect of these particular products is that they are not traded bilaterally and participants do not need to have physical generation assets. This brings much needed liquidity to the market. In later chapters we will demonstrate in detail how these variables can influence the electricity price. First, a brief explanation about the general electricity market structure and some key market fundamentals which will set the foundation for the rest of the dissertation are given.

The market design concepts, data, and analysis presented in this dissertation are based on data related to the Midwest Independent Transmission System Operator (MISO) Market and Cinergy hub. Nevertheless, the market concepts and analysis presented in this dissertation can be generalized and are applicable to any electricity market in US.

2.1. ELECTRICITY MARKET STRUCTURE

An organized electricity market consists of Independent Transmission System Operators(ISO) or Regional Transmission System Operators (RTO), Generation Companies (Genco), Asset Owners, Load Serving Entities (LSE), Power Marketers, Trading Exchanges and Market Makers. These entities are discussed further in the following pages. There are authorized electricity markets which do not have any ISO or RTP status.

The Independent Transmission System Operators (ISO) or Regional Transmission System Operators (RTO) are not-for-profit organizations whose primary job is to coordinate all the transmission systems, balance power flow, manage congestion and deliver load across their respective footprint. These organizations ensure safe, cost-effective and reliable delivery of electric power. The ISOs and RTOs also offer an organized market which helps the market participants trade electricity and manage the risk associated in electricity market. The ISOs and RTOs are usually supported by their stakeholders. The stakeholders are usually the generation and load distribution companies as well as other market participants who are for-profit organizations. The ISOs and RTOs are approved by the Federal Energy Regulatory Commission (FERC) and the North American Electric Reliability Corporation (NERC).

The Generation Companies or Gencos are the corporations which own any form of electricity generation unit. The Load Serving Entities or LSE are the ones who serve load to a large customer base and serve as an intermediary between the Gencos and the customers. A market participant does not necessarily have to own a generation unit. The trading exchanges and market makers facilitate a system where participants can trade electricity related products. This attracts a large number of financial institutions and hedge funds into the electricity market. Their involvement increases the much needed liquidity in the electricity market.

Currently, there are five ISOs overseeing transmission grids and electricity flow across US. These are the California ISO (CAISO), New York ISO (NYISO), ISO New England (ISO-NE), and Pennsylvania-New Jersey-Maryland-ISO (PJM). However, for a Genco or LSE, participation is not required in a particular ISO or RTO. There are plenty of bilateral arrangements that still supply electricity across USA. The market is hopeful that it will change in the near future as the market matures and participants become more experienced with centralized power markets. Figure 2.1 shows different organized electricity markets across US. Please note that the Northwest, Southwest, and Southeast markets are not considered either as ISO or RTO. The ERCOT and SPP are examples of RTOs. Figure 2.2 shows the Midwest Independent Transmission System Operators (MISO) footprint. Participating Gencos, LSEs and other market participants across this vast footprint trade energy and energy related products in MISO system.

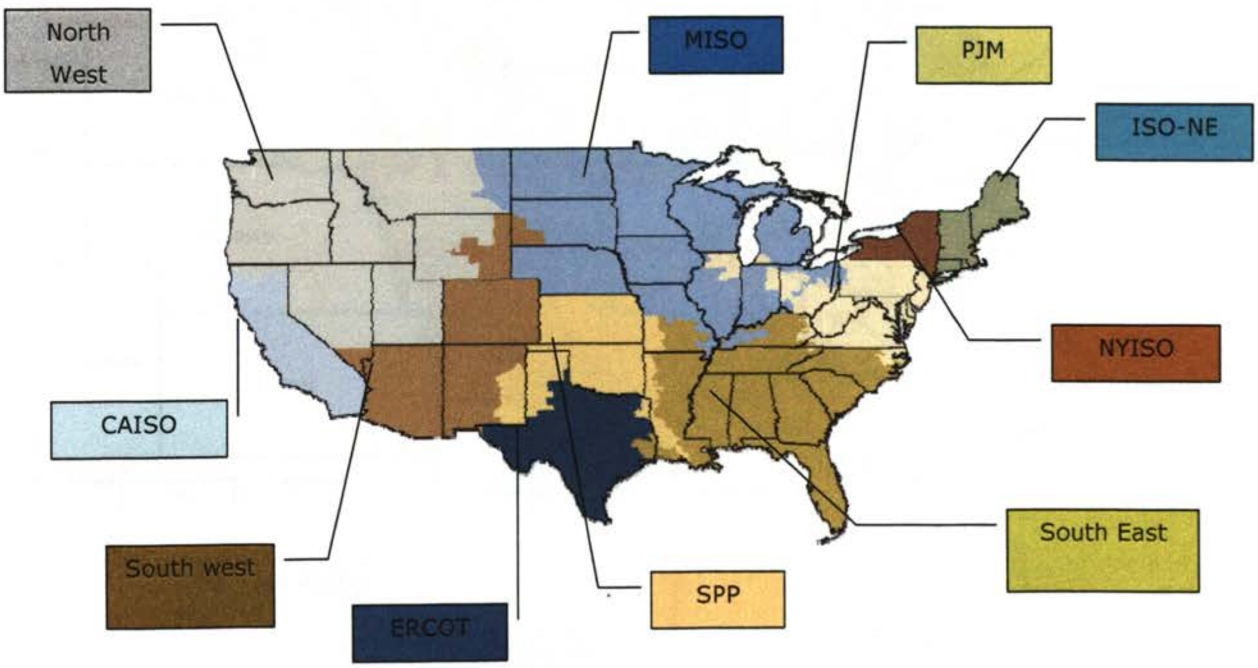

Figure 2.1. Electricity Markets across USA

Source: Federal Energy Regulatory Commission's (FERC) webpage
Web address: http://www.ferc.gov/market-oversight/mkt-electric/overview.asp
Last visited: June 20, 2008)

In the following section, some fundamental mechanisms and characteristic of the electricity market are discussed.

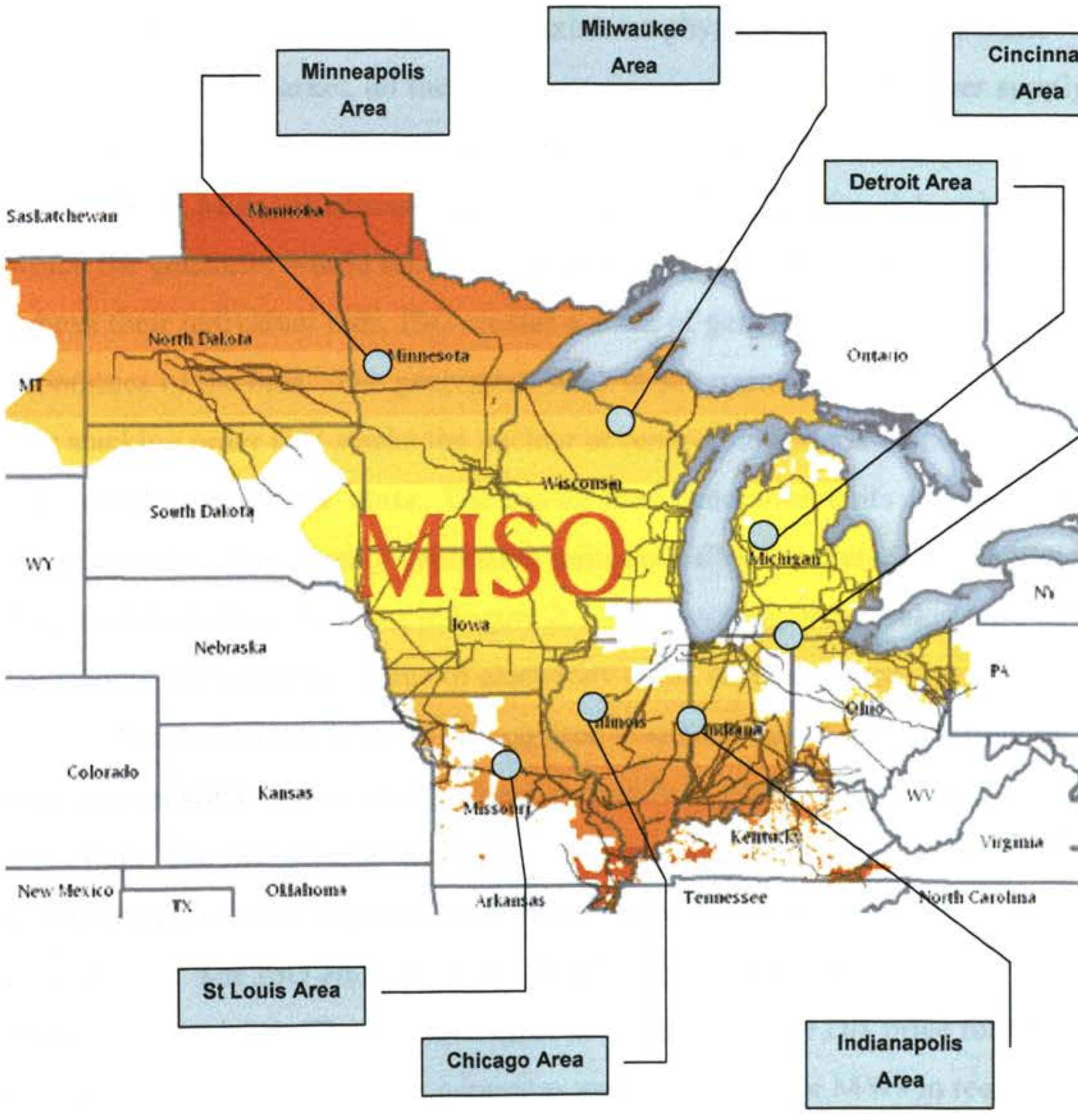

Figure 2.2. MISO Footprint Indicating Some Important Constituent Cities

*(Source: http://www.platts.com/Resources/map/images/MISO_525.gif
Last visited: June 20, 2008)*

2.1.1. Day-Ahead (DA) Market. The Day-Ahead (DA) market works as a forward market for electricity in which market participants can buy and sell energy prior to the operating day. An operating day denotes the market date or the trade date in which the market is operating. The DA market provides an opportunity for the participants to hedge against possible spikes in the Real-Time (RT) electricity spot price. Clearly, the DA market is purely financial as there exists no physical generation or load.

In the DA market, all the market participants submit their power supply bids to the Independent System Operators (ISO). The bid is a function of the cost and volume (Harris 2006, MISO Business Practice Manual[1]). This function determines the price at which the generator would supply the megawatts (MW). Once all the market participants submit their individual bids, ISO creates a stack of generation units based on the economics of the bids. The generation stack is determined primarily by the fuel type. The stacking order first stacks the nuclear or renewable generation sources. These units are termed as 'must run' units. The gas/oil fired generation units are placed higher in the stacking order. These costly generation units are called 'peakers.' A schematic view of the generation stack is shown in Figure 2.3. The stacking order makes sure that the consumers have reliable source of electricity at the cheapest price.

The market participants are required to submit their bids and offers by a certain timeline, mostly in the morning. These contain both physical and financially binding bids and offers. The ISO awards the MWs to different generation units based on their security-constrained economic dispatch model to ensure that the cheapest generation units are cleared first. The ISO announces the award details in the same afternoon the bids and offers are submitted. The awarded units are guaranteed the DA price for the MWs they are awarded as long as the unit generates and dispatches the MWs in real time.

2.1.2. Real-Time (RT) Market. The Real-Time (RT) Market acts as a balancing market between what has been cleared in the DA Market and the actual RT energy consumption or load. The ISOs run the Economic Dispatch program every five minutes of the operating hour to generate dispatch instructions for generators to meet the future load of the next five minutes. Figure 2.4 shows how DA and RT markets operate.

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[1]MISO Business Practice Manual or BPM can be found at http://www.midwestmarket.org/publish (Last visited: June 20, 2008)

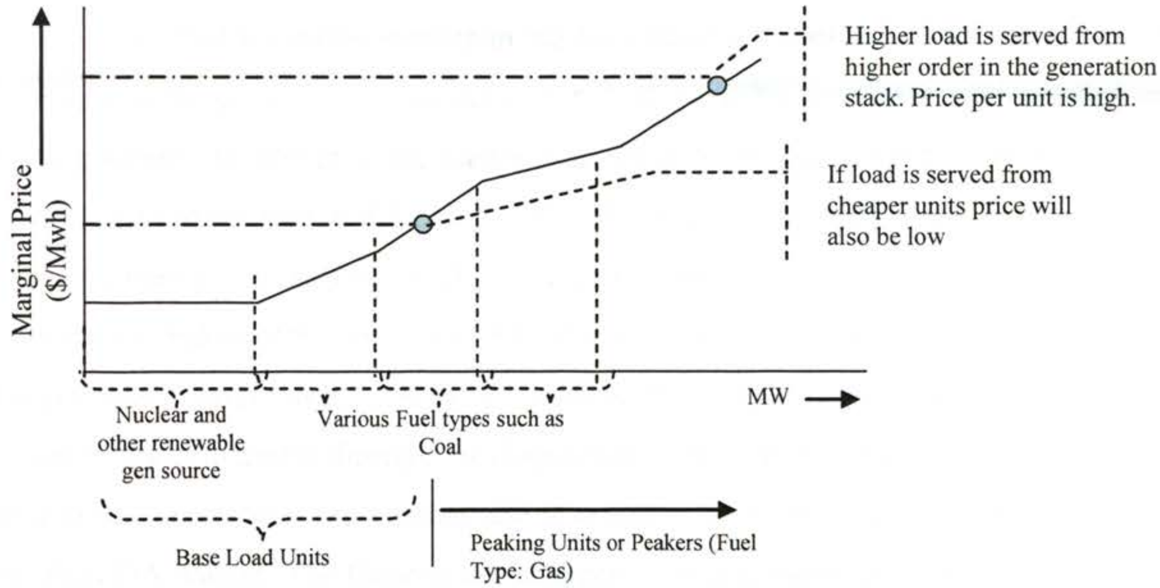

Figure 2.3. Generation Stack

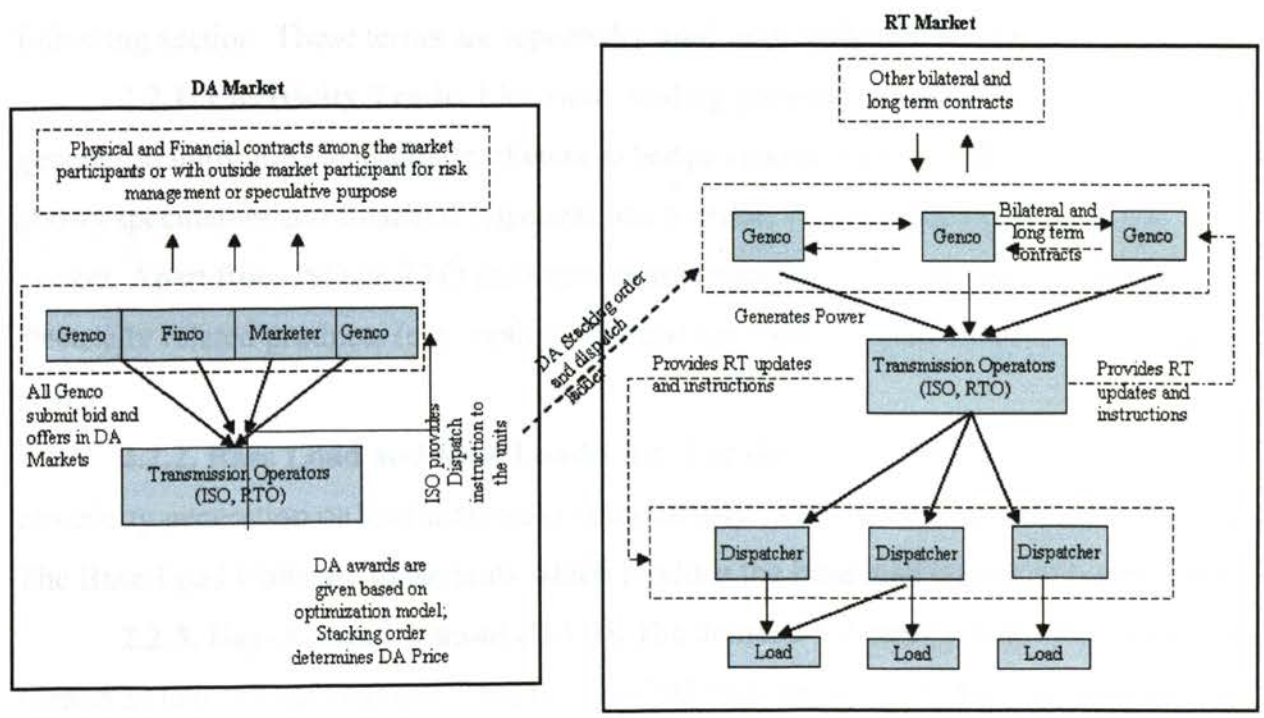

Figure 2.4. DA and RT Market Operation

If the load increases more than the forecasted demand in the real time, the ISO may instruct the generators to produce more MWs and the generators are awarded make whole payment. However, if the load is less, the generator pays back to the ISO for the unused MWs at the rate of RT price. The DA market participants may have bilateral contracts among themselves. Such existing contracts may influence the DA market participants' bid or offer decisions. The dispatch ladder or stacking order issued in DA market goes in effect in RT. In the RT market, the Gencos produce electricity which is served to the consumers through the dispatchers. The ISO provides RT updates the RT need to the dispatchers and Gencos and instructs if the Gencos should produce more or less than DA Award. The Gencos can also serve other commitments they may have in RT. The Genco may decide to buy power from some other Genco instead of producing and serve its commitments to the ISO.

2.2. KEY DEFINITIONS

Now, some key definitions for the electricity market are presented in the following section. These terms are repeatedly used later in this dissertation.

2.2.1. Electricity Trade. Electricity trading provides an infrastructure for the generation units and electricity marketers to hedge against various risks. The market also allows speculators and financial organizations to trade, which bring liquidity to the market. Apart from ISO or RTO platform, many financially and physically binding electricity related products (e.g., options, swaps) are traded in Intercontinental Exchange or ICE.

2.2.2. Base Load and Base Load Unit. The Base Load represents the amount of electricity generation or load that exists continuously in the market during a given period. The Base Load Units are those units which produce the base load on a continuous basis.

2.2.3. Day-Ahead Demand (DAD). The demand for energy in the DA market is termed as Day Ahead Demand (DAD). The DAD for energy is the forecasted value for the next day's RT load. The cleared DAD contains fixed and/or price-sensitive demand bids. The demand is different from the load. However they are expressed with the same unit. The usual unit measurement for DAD is kilowatts (KW) or megawatts (MW) or gigawatts (GW).

2.2.4. Real Time Load (RTL). The actual amount of energy that being consumed by the customer.

2.2.5. Native Load (NL). The native load or NL is defined as the load consumed by a utility company's retail customer base.

2.2.6. Hour Ending (HE). Since most of the electricity trade is indicated on hourly basis, the term "hour ending" is commonly used in the market. HE denotes hourly time blocks starting from midnight. For example, the hour following midnight is HE 1, and the hour between 1 am to 2 am is HE 2. The hour that ends at midnight is denoted as HE 24.

2.2.7. Locational Marginal Price (LMP). LMP is nothing but the market clearing price for energy at a given location at any given hour. Clearly, they vary from location to location. In this dissertation, without loss of generality, it is assumed that the LMPs are quoted and reported on hourly basis. The LMPs are observed in both DA and RT market and are denoted as DA Price or DA LMP and RT Price or RT LMP, respectively.

2.2.8. Commercial Pricing Node (CPNode). The CPNodes are aggregate price for one or more Elemental Pricing Nodes (EPNodes).

2.2.9. Peak/Off Peak Periods. The Peak period or Peak Hour is the time of the day when the load is expected to be at its maximum. Usually the 16 hour block from HE 7 through HE 22 during the weekdays (Monday through Friday) except NERC listed holidays are considered as peak hours. The off-peak hours are the remaining 8 hour period during the weekdays or 24 hour period during weekends or NERC listed holidays. The Peak/Off peak Hour time block changes along with the day light savings time shift. Later in this dissertation, we will analyze how peak/off-peak periods affect the load and price.

2.2.10. Long and Short Position. A long position indicates that the company has enough generation resources to meet the load. A short position indicates the opposite. The short position indicates that the company does not have enough resources to meet its sales position. Usually the generation companies are always long as they have the generation resources to meet the demand.

2.2.11. Heating Degree Days (HDD) and Cooling Degree Days (CDD). The Heating degree day (HDD) and the cooling degree day (CDD) are defined as the difference between 65°F and the average outside temperature for that day. The HDD and CDD indicate the demand for energy on a given day.

2.2.12. Swap. The Swap is a bilateral agreement between two counterparties to exchange physical electricity or settle for cash only during the agreed time and hours. In this contract the buyer of the swap deal pays to the counter party at the time of agreement and the counterparty pays when the contract actually is settled. In electricity market, swap deals can both physical and financial. Most of the Swaps are traded in ICE platform.

2.2.13. Virtual Bids and Offers. Virtual bids and offers are financial instruments provided to the market participants that allow the participants to bid to buy or offer to sell MWs in the DA market. Virtual bids allow the participants to buy "virtual megawatts" in the DA market and virtual offers allow the participants to sell "virtual megawatts" in the DA market. The assumed position in the DA market automatically reverses back in the RT market. The settlement is the difference between the DA and RT prices observed at the particular node where the virtuals are awarded.

2.2.14. Basis Risk. The basis risk is defined as the difference between prices. The basis risk can be of two types—locational basis and time basis. The locational basis is defined as the difference between the prices observed in two different nodes or locations. The time basis is defined as the difference between the forward and spot price or difference between the DA and RT price observed at a particular node.

2.2.15. Hub. It is a CPNode that represents an aggregate price for a collection of EPNodes. Cinergy hub or Detroit hub are typical example of hubs. Essentially, the hub is a node or location on the power grid which represents a delivery point. Power traded with reference on a particular hub changes ownership at such node or hub. Clearly, the hubs support bilateral trading among the market participants which brings more liquidity to the market. Figure 2.5 shows 10 major trading hubs in US. Five of these hubs are located in the western part of US, four in the Midwest region, and one in the east. There are, however, many other small nodes in the electricity grids which also act as hubs. Many financial products refer to the major hubs for a price reference for the settlement purpose.

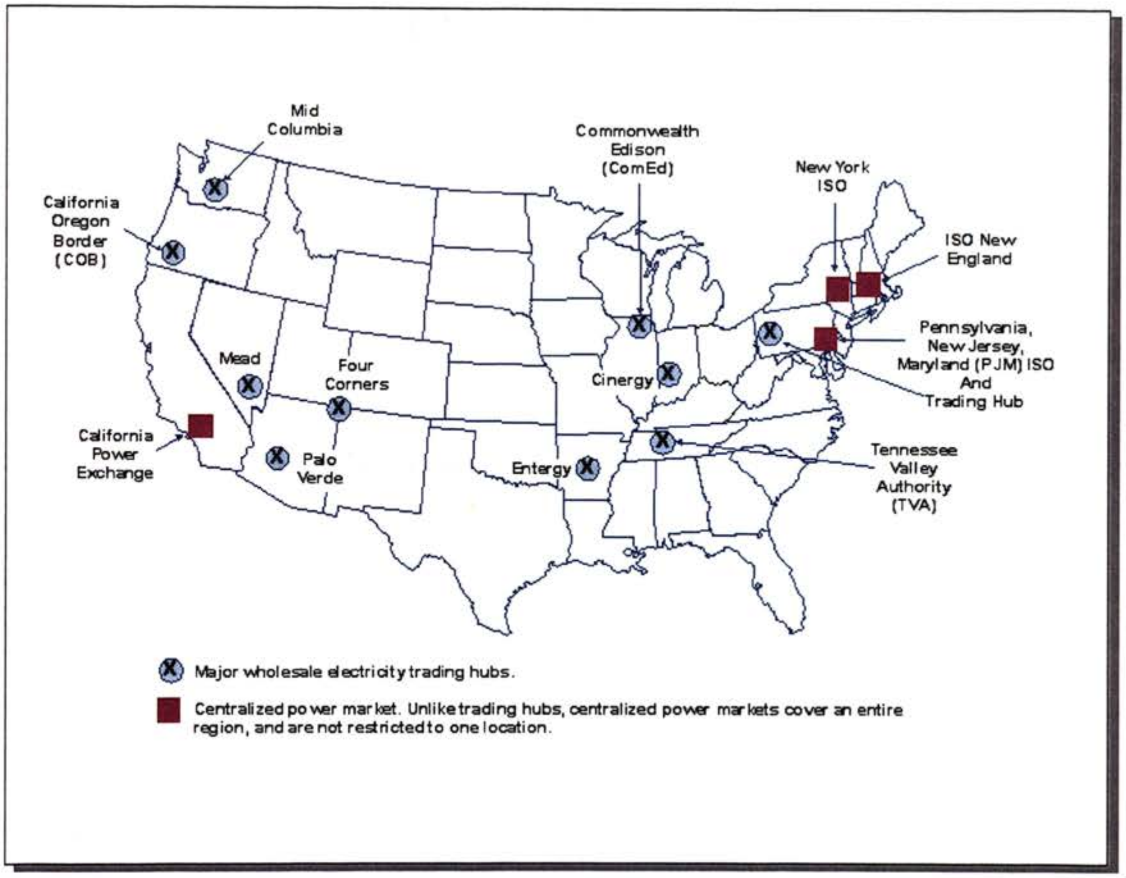

Figure 2.5. Major Electricity Trading Hubs across USA

(Source: Energy Information Administration (US Dept. of Energy)
Web: http://www.eia.doe.gov/cneaf/electricity/chg_stru_update/fig28.html
Last visited: June 15, 2008)

3. LOAD MODELING

3.1. INTRODUCTION

Understanding how the load and demand behave and producing accurate model for these are very important for those dealing with the electricity market. A better model helps in better planning and reliable load generation. According to a survey conducted in UK, even one percent increase in the forecasting error can increase the net operating cost by almost £10 million (Guo, et al. 2006). A good model captures the general trend in energy consumption as well as the impact of sudden weather changes on energy demand.

Demand, as mentioned in Section 1, represents the DA Demand (DAD) or the forecasted value of the Real Time Load (RTL). The word "load" is used in RT to indicate the power consumption in the market. In the past decade, especially after certain electricity markets have been de-regularized and financial markets for electricity trading have flourished, load forecasting has become more important. In this chapter, the literature on the load forecasting models as well as the variables that directly affect the DAD and RTL are discussed. We first present some DAD and RTL data from the MISO market and patterns one can observe in this data. This will help us understand how demand and load pattern varies time to time.

In general, the daily electricity usage pattern follows a very usual shape (see Figure 3.1). Starting at HE 1 (1:00:00am), the demand load drops until the early morning time and gradually peaks up again. The load reaches its peak sometime in the afternoon and gradually drops back to its original position. This is not surprising if one considers people's daily life-styles. Usually peoples' needs for electricity starts early in the morning when they prepare to go to work. Offices and factories resume their regular working hours during the morning causing the load to peak up. As the day progresses peoples' need for energy also increases. However, the load peaks in the late afternoon when people return home. During this time, the office lights are still on and the household energy needs kick in. Figure 3.1 shows a typical load profile for a 24 hour period and how it varies on a single day. Figure 3.2 shows co-movements of the DA demand and RT load for one week period in August 2007.

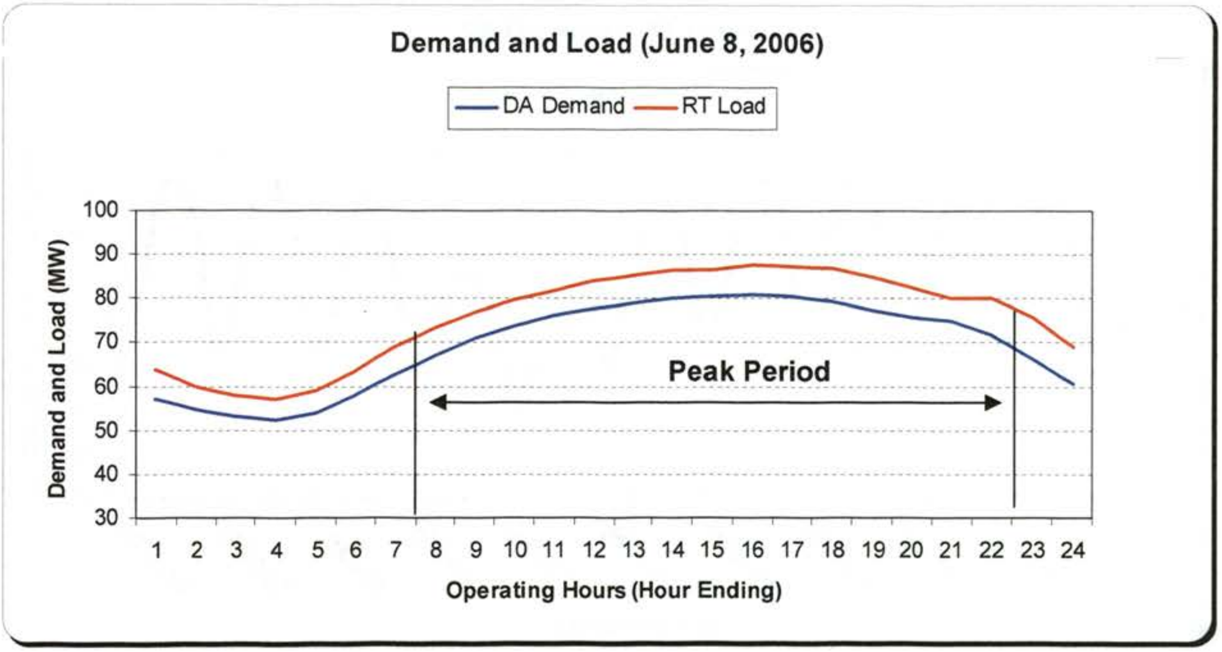

Figure 3.1. Hourly DA Demand and RT Load (June 8, 2006)

Since DA demand is market's forecast about RT load, it follows a similar shape. However, the actual values could be different depending on the weather and other variables. In the following section, some key published studies on electricity load will be studied. This will help us understand precisely why the DAD and RTL may be different.

3.2. LOAD MODELS

Generally, the load forecasting models can be classified into three segments—short term (one hour to a week), medium term (ranging from one month to up to a year or even up to three years), and long term forecasts (over three years) (Willis,1996). Also, all the load forecasting models can be classified as statistical, mathematical, econometric, and others (Feinberg, Hajagos, and Genethliou (2002, 2003)).

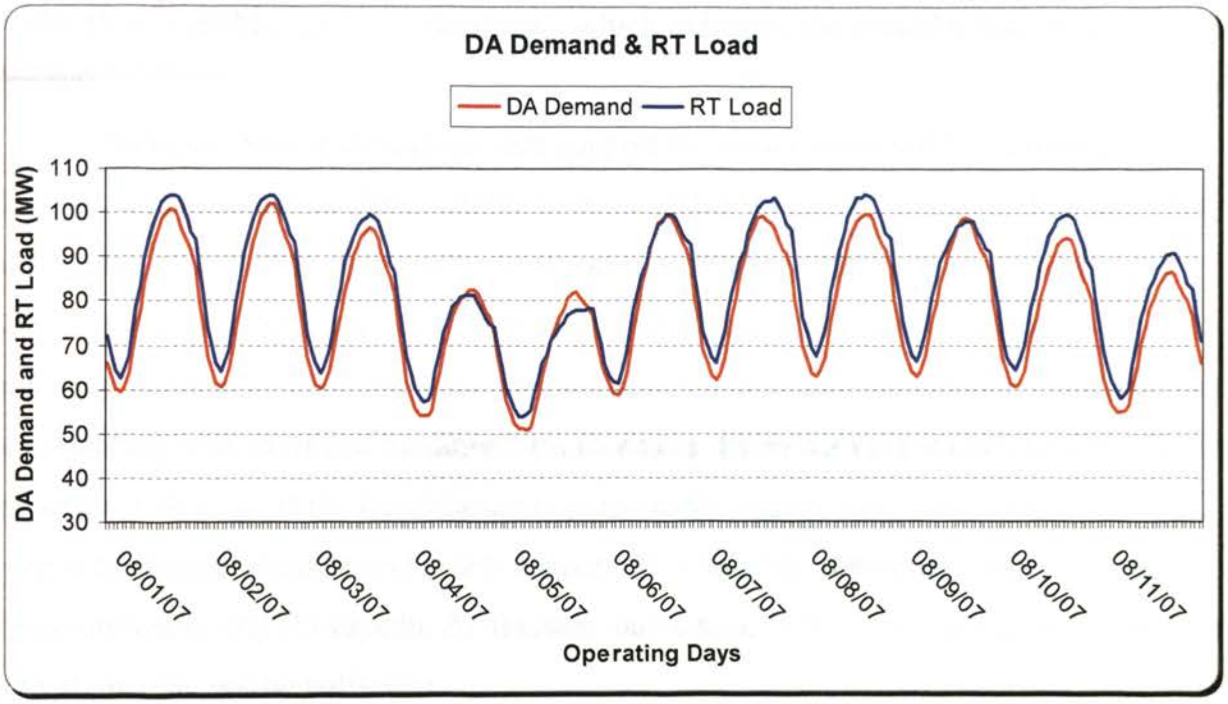

Figure 3.2. DA Demand and RT Load (Aug 1-Aug 11, 2007)

Feinberg, Hajagos, and Genethliou (2002, 2003) developed a statistical model for a load pocket incorporating weather parameters, the day of the week, and the hour during the day. They defined the load pocket as an area which does not have sufficient transmission capability to support 100% of the electric load without any disruption and dependency on generation resources physically located within that area. Feinberg, Genethliou, and Hajagos (2002, 2003) included four different weather parameters — temperature, humidity, sky cover, and wind speed for their load model. The models are based on a set of linear regressions. The regression based load forecasting model developed in this paper uses historical weather and load data from several load pockets in the Northeastern part of the USA for several consequent years. The weather variables include temperature, humidity, wind speed, sky cover, and variable sunshine. The time variables consist of a day of the week, or a holiday, and an hour during the day. In their model, Feinberg, Hajagos, and Genethliou (2002, 2003) used a new variable which is a multiplicative form of daily and hourly load component and weather factors. Feinberg, Hajagos, and Genethliou (2006) extend their previous work by adding one more explanatory variable, namely "sunshine," which indicates the period when the sun light appears.

There are other publications that support the views proposed by Feinberg, Hajagos, and Genethliou (2002, 2003) on the weather variables. Load models provided in Douglas et al. (1998), Owayedh, Al-Bassam, and Khan (2000), Taylor and Buizza (2002), and Dong, Xu, and Teo (2003) show that climate data such as temperature, humidity, dryness or even sunshine are important input to any load model, especially the ones dealing with short and medium term forecasts. Even human psychology can play an important role (e.g.: if the temperature is consistently higher for a period of time, then even if the temperature drops by few degrees for a day, the consumers may not turn the air-conditioners off) (Owayedh, Al-Bassam, and Khan, 2000). So, using the temperature data alone may not be sufficient.

It is important to note that an increase or decrease in the temperature may not always change the load shape from its historical pattern except for some summer days and some winter days when the climate conditions are quite different from rest of the year. As shown in the Figure 3.3, if the temperature change is between 55°F and 70°F, the change in load is not significant. Figure 3.3 shows the MISO RT load and daily average temperature across Cincinnati, St Louis and Minneapolis. Mirasgedis et al. (2006) show a similar effect of temperature data on load observed in Greece. According to their finding, the load fluctuation is more sensitive to the temperature change during summer compared to winter (except in cases of severe winter weather). Moreover different load classes have different sensitivity to temperature (Eydeland and Wolyniec,2003; Mirasgedis et al., 2006). For example, the industrial load shows lowest sensitivity to temperature fluctuation whereas the residential load shows highest sensitivity to temperature (Eydeland and Wolyniec,2003).

In their research, Feinberg, Hajagos, and Genethliou (2002, 2003) originally included the temperature, humidity, sky cover, and wind speed; however, not all these variables were statistically significant for the load data they tried to fit. After trying different combinations, they report that temperature, humidity, wind speed along with a new variable called sun-shine can significantly explain the load in their model.

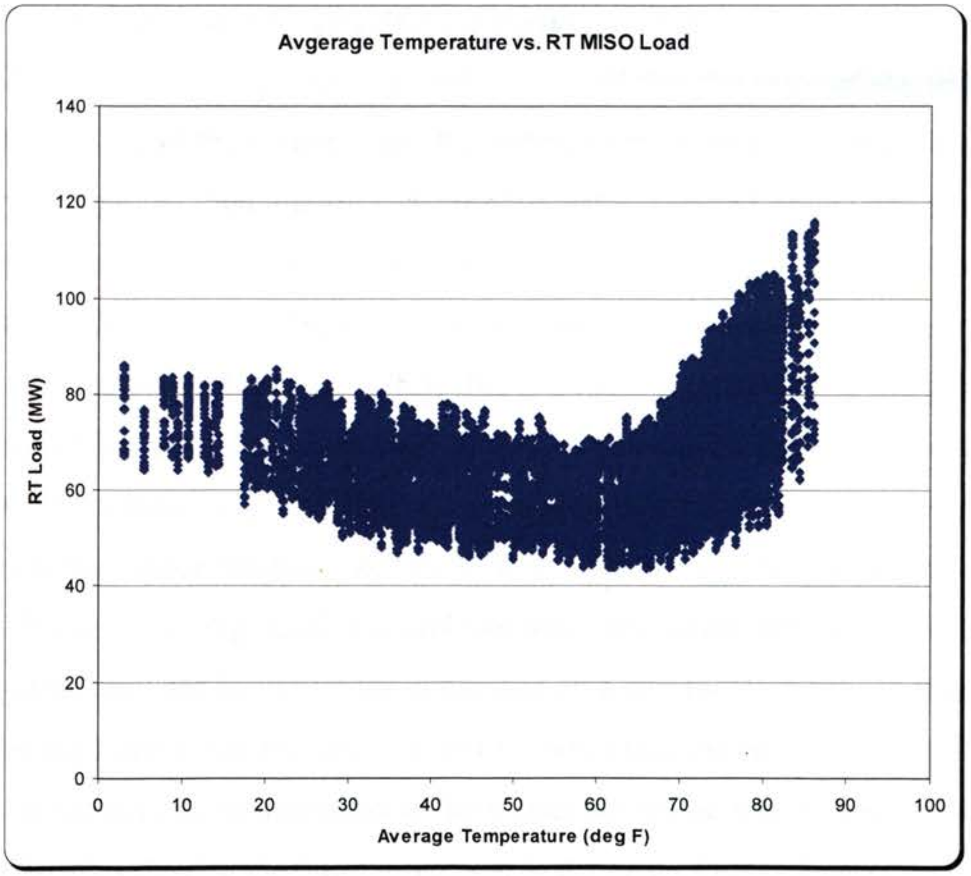

Figure 3.3. Real Time Load vs. Average Temperature

Chen, Canizares, and Singh (2001) proposed a model based on Neural Networks to forecast short-term load. The authors considered the electricity price as one of the main factors in determining the load. They described the system load at any given time as a combination of four different components—normal part, weather-sensitive part, special event part and a random part. The normal part is nothing but a set of standardized load shapes. The load shape is classified based on the "type", which is recurring throughout the year. This takes care of the daily pattern observed in the load shape. The weather-sensitive part represents the seasonality of the model. The special event part signifies any unusual event that can cause a significant deviation in the load pattern. Finally, the model adds a random part represented by a standard zero mean white noise process and signifies the randomness in the load pattern.

Chen, Canizares, and Singh (2001) presented a different approach compared to other load forecasting publications. The authors argued that the price of electricity can also considerably affect the system load. According to the authors, the price elastic customers would adjust their energy consumption patterns based on the price level to reduce energy cost from the monthly bill and to maximize savings. Based on this argument, the authors produced a non-linear relationship between the system load and the factors influencing the system load. While this is a valid argument for a long term purpose, this is not a strong and necessary argument that can be applied without loss of generality to DAD modeling. This theory can be applicable mainly in deregulated markets where the customers have the option to see the energy price as they use the electricity. However, in regulated markets like Missouri, customers paying a fixed price for consumption may not be very price conscious on a day-to-day basis. A study published by the Edison Electric Institute (EEI) shows that the electricity consumption has increased (which can be attributed to the higher economic and demographic growth) in past two decades despite the huge increment in the cost of natural gas, crude oil and coal.

Nowicka-Zagrajek, and Weron (2002) presented a pure statistical model for the load forecasting based on the ARMA process. The data used in their paper is collected from the California power market. The authors fitted an ARMA(1,6) model. The data set included load information for every hour between April 1st, 1998 and December 31st, 2000. Since electricity load data exhibits a strong daily cycle, the authors created a 1006 days long sequence of daily loads. The authors also founded weekly and annual seasonality. They authors used the spectral density technique (Periodogram) to detect the seasonal pattern in the dataset. Their analysis showed well-defined cycles with period 7 and 365 days and smaller peaks close to periods of 3.5 and 2.33 days. The seven day cycle which is not sinusoidal also exhibit lagged autocorrelation. The authors removed the weekly cycle with moving average (MA) techniques; however, they could not remove the annual seasonality using the same techniques as they did not have enough data to support it. Their paper proposes a new scaling method in which the logarithmic return value of the load data is divided by a smoothed annual volatility. The ACF and PACF[2] of the newly derived time series with the smoothed data (considered to be a stationary process) rapidly converge to zero suggesting that a mean corrected ARMA processes can be fitted. AIC[3] was used to select the best fitted model. They fitted a hyperbolic distribution to the residuals obtained after the ARMA fit because the residuals seem to exhibit tails heavier than the Gaussian distributed error.

Most of the load forecasting models discussed in the previous section have used only a single point weather forecast as an explanatory variable. However, it is important to understand how weather variables could change during a particular day and how different weather scenarios could change the load shape. Such shortcomings of the forecasting models can be overcome by the model proposed by Taylor and Buizza (2002). These authors proposed a demand forecasting model to forecast the load for one day up to 10 days ahead using weather ensemble predictions. The weather ensemble helps to produce 51 different scenarios for the weather-related component of electricity demand. The authors proved that the average of these ensemble generated scenarios produces more accurate forecast than the forecast produced by traditional weather forecasts. The paper used the weather ensemble predictions for temperature, wind speed and cloud cover. The forecasts were produced for lead times from 12 hours ahead to 10 days ahead. The paper uses ensemble predictions produced by the European Centre for Medium-range Weather Forecasts (ECMWF) between 1 November 1998 and 30 April 2000. However, since ensemble predictions were available only for midday, the model discussed in this paper is able to forecast the load only for the midday period. While this is a significant drawback, the authors argue that midday often represents the peak hour during several summer months. This may be true for the geographic region the data represents; however, it may be different in other geographic locations. The authors use the 51 different ensemble scenarios for temperature, wind speed and cloud cover to substitute in the *weather-related demand* expression. This substitution produces 51

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[2] ACF or autocorrelation function describes the correlation between two different points in time of a given process. PACF or partial autocorrelation function of order k describes the correlation between two points beyond k lagged terms in the time series data.

[3] Akaike's Information Criterion or AIC is used as selection criterion among many nested econometric models. It was originally proposed by Professor Akaike in 1974 as a measure for statistical model fit.

scenarios for the weather-related demand. Then the probability density function for the demand is constructed using the 51 different scenarios. The estimate of the mean is considered as the mean of the 51 different weather related demand scenarios.

Most of the load research literature devote time and energy in building models with weather, and other explanatory variables such as day, week, season, holiday etc. The methodologies used vary from statistical (e.g.: regression analysis and time series) to machine learning algorithm to neural networks. However, one completely different, yet significant, approach could be to take meter reading data of different household and their electrical appliance usage pattern and model the demand function. Paatero and Lund (2006) propose a similar idea where the load is constructed using elementary load components such as load from households or even from individual appliances. The authors called their approach a "bottom up" approach as the data used is at the user end. The model proposed in this paper can be used to generate the domestic electricity load forecast on an hourly basis from a few up to thousands of households. The main advantage of this proposed model is that it has been constructed using publicly available reports and statistics on electricity consumption.

The biggest drawback, however, for the above approach is that while trying to understand the overall market load and demand, households represent only a fraction of the overall load. The model proposed by Paatero and Lund (2006) has two parts. The first part addresses the general fluctuation of diurnal consumption levels and separate appliance stocks for each household. The second part attempts to simulate the usage of each appliance in the household. Essentially the first part of the model determines the daily values of social random factor and the second component of the model signifies the electricity consumption profile of each individual appliance at different time space.

The load models described above aim to accurately forecast future load based on currently known data. For example, to forecast the load at 5 pm tomorrow, one has to use the forecasts of temperature as well as other variables such as humidity, and sunshine for that time. Such models are important for determining DAD and making bids and offers for electricity for a given hour in the future. The load models developed for this dissertation have a different goal. The aim is not to forecast tomorrow's load using data that is available today, but to model the behavior of the hourly load so that the resulting model can be used to simulate hundreds of feasible load patterns, each patterns a realization of the infinite number of patterns that are statistically possible. Each hedging strategy can then be tested on each of these "virtual" time series and the net gain or loss averaged over the ensemble of the generated series, thus giving us an estimate of the expected gain or loss across all possible scenarios. One can say that what is needed to satisfy this objective is a model that explains how past load values as well as real-time variables such as current temperature and humidity affect current electricity load. Such a model should also take into account seasonal variations, daily cycles, as well as autocorrelations among the stochastic components. In addition, such a model should allow for stochastic variations, not only in the error component, but also in the seasonal and cyclical parts as well. The Unobserved Components Models (UCM) with input variables such as lagged load, temperature, humidity, fit these requirements and thus utilized for modeling RT Load and DAD.

In this section a variety of hourly, short term and long term load models have been discussed. These publications propose a wide variety of methodologies—from expert systems (Irismi, Widergren and Yehsakul , 1992) to Artificial Neural Networks (Peng, Hubele and Karady, 1993; Chow and Leung, 1996; Chen, Canizares, and Singh, 2001; Taylor and Buizza; 2002) to time series modeling (Nowicka-Zagrajek, and Weron; 2002, Feinberg, Hajagos , and Genethliou, 2002). Each publication claims to have strong results. Many of them use virtually the same type of explanatory input variables and almost all the models have a good fit. These methodologies are of particular interest because of the non- linear relationships we observe between the load and different explanatory variables. However, these sophisticated models are complex and are subject to over fitting. These models are also computationally cumbersome. The over fitting of a time series results when the methodology models the random "noise" component of the process as part of the "signal." The use of a model estimated by complex non-linear methods such as neural nets for simulating feasible hourly load patterns for a hypothetical year is inappropriate because the over fitting "locks-in" at least part of the noise component as a "signal" and therefore will not allow the simulation process to generate time series with the full variability that is naturally present due to unobserved factors. For use in a simulation study, one needs a model that captures (1) the seasonal patterns, (2) the daily consumption patterns, (3) the autocorrelation between time series values that are temporally close, and (4) the relationship between weather variables and load, while allowing the measurement of the variability of the noise component so that this noise can be generated as a random process during the simulation study.

As mentioned in Palacio and Edenor (2001) and London (2007), weather changes month by month and week by week. Weather pattern also shows significant difference across the geographic locations. The models proposed in this dissertation not only capture the seasonal and cyclical pattern of the weather on historical basis, but also include the variability in weather across the MISO footprint. Since hourly observations of the climate data are not available, this dissertation does not include hourly observation to improve the model.

4. PRICE MODELING

Section 3 discussed different aspects of the load and demand profiles and publications on load forecasting models. In this chapter, the DA and RT price processes will be discussed.

4.1. ELECTRICITY PRICE MODELING

The electricity price is governed mainly by the demand for energy and supply of electricity that is available to satisfy that demand. Both are stochastic in nature. Typical electricity markets in the US have two settlement systems and therefore observe two different prices, namely DA LMP or DA Price (DAP) and RT LMP or RT Price (RTP). In this dissertation, we will use either the LMP or Price to denote electricity price without loss of any generality. As shown in Figure 1.3, DAP is observed in the DA Market and RTP is observed in the RT Market. While DAP is primarily a function of the DA Demand and Supply Curve (or, Generation Stack), later we will discuss how market makers in electricity market can influence the DA price. Similar theory counts for RTP too. From this fundamental understanding, it is clear that the load is the key determinant for price.

The Locational Marginal Price or LMPs observed in the hubs such as Cinergy hub or PJM West hub are the arithmetic average of LMPs in nodes coming to the hub. By definition, the locational marginal prices indicate the cost of generating and supplying the block of electricity at those locations. LMPs include three components—marginal cost of energy, congestion cost and transmission losses. The LMP gives a precise and market-based method for pricing energy that includes the congestion cost and transmission losses. The ISOs first clear the marginal and cheapest units such as nuclear, hydro and wind. Renewable generation units are called must run units. Next in the generation stack are more expensive coal or oil fired units and then the gas fired units (called peakers) which are most expensive to run. All the units up to coal in the generation stack are considered base load units. If a base load unit does not clear in the market or if all the base load units do not meet the demand, then there may be a price hike as the market will consume from upper level of the generation stack. The LMPs during the off peak hours are usually lower than the peak hours as the cheapest units are in service. The peakers are usually utilized during the peak load and considered as price setters in the market (Nagarajan, 1999). This is because less expensive units such as nuclear, hydro or coal fired generators are cleared first in the generation stack and are used during the off peak as well as peak hours. Generally, the peaking units are used when the load increases. The market participants offer their generation at least "at cost" or "at cost plus mark up" price. The forward market price of natural gas has a strong correlation with the forward market price for power (especially during the peak hours) [Nagarajan, 1999; Skantze and Ilic , 2001; Eydeland and Wolyniec, 2003]. Clearly, the cost of gas, coal or oil indirectly set the market price of electricity. As the cost of natural gas or oil or coal increases, the cost per megawatt in the generation stack becomes costlier and therefore, it raises the price of the electricity in both DA and RT Market. Therefore, the price of electricity can be expected to increase over a period of time if the cost of gas, oil or coal increases.

As mentioned earlier, Smith (2000) also agrees that load is a key determinant for the price movement. Figure 4.1 shows the empirical relationship between price and load. The higher the demand is the higher the expected spot price of the electricity is. As seen in Section 2 and as shown by Smith (2000), electricity load follows strong daily, weekly, and yearly cyclical behavior, and has strong correlation with weather parameters. The load profile can also be identified by geographical regions. This suggests LMP forecasting should have also become easy. Nevertheless, weather parameters that play crucial role in load modeling are very unpredictable. Research conducted by Floehr (2003) shows that the "best" weather forecasting service has approximately 24.68% of RMSE[4] on the temperature forecast over the year. Moreover if the weather prediction has higher errors, the load prediction will not be correct. Therefore traders will not have best understanding of the price. Also, unlike other commodity prices, the electricity price depends a lot on congestion, unit outage etc. making it harder to forecast the price very precisely.

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[4] RMSE stands for Root Mean Square Error

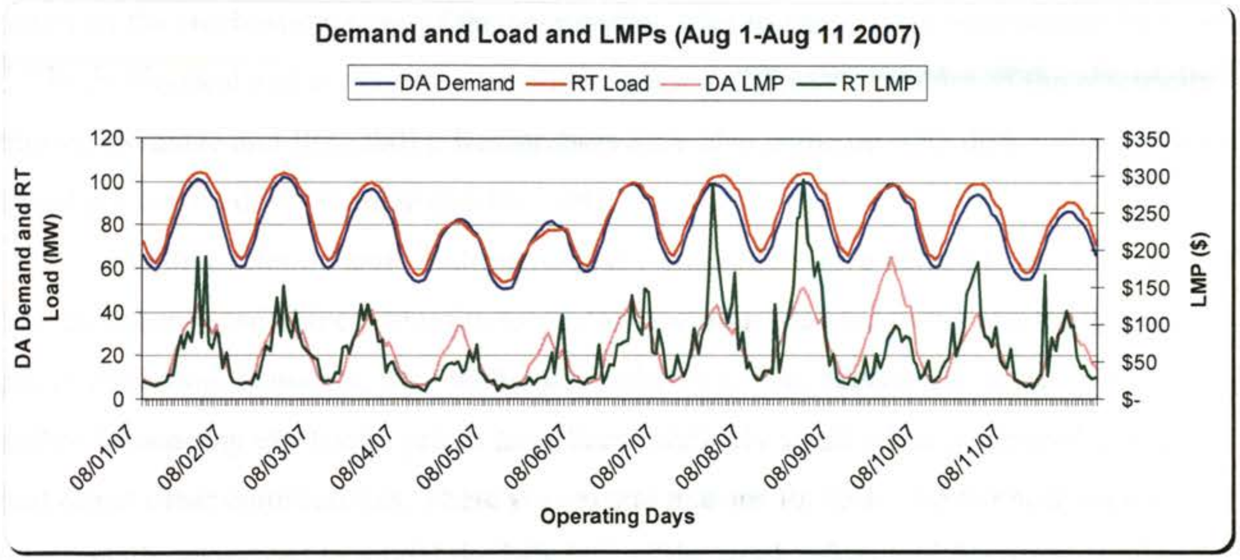

Figure 4.1. Load and Price Relationship

There are different types of pricing models available—statistical, production cost base, economic equilibrium based, agent based, and fundamental models (Skantze and Ilic, 2001). Each has its own merits and disadvantages. Statistical forecasting models are generic and attempt to capture the stochastic properties of the price (Skantze and Ilic, 2001). These models usually capture price movement pattern based on historical trends and cycles. However, the electricity price is governed by many different factors other than just the market based economy which creates a need for other types of models (Skantze and Ilic, 2001; Eydeland and Wolyniec, 2003). The production cost based models look at the marginal cost of production and determines the price based on the cost based bidding (Skantze and Ilic, 2001; Eydeland and Wolyniec, 2003). These models essentially look at the demand and supply functions and set the market price. However, they ignore strategic bidding or any kind of gaming intended by the market participants. Also, the diverse participant pool (such as financial institutions or hedge funds that may not have any generation units and participate in the financial market of the electric market) and their playing strategies are not captured by the cost based models. Economic equilibrium models do consider the market forces and their strategies along with the cost model (Skantze and Ilic, 2001). The fundamental modeling of electricity prices which is based on the stochastic nature of the commodity, tries to capture the relationship between the basic physical and economic relationship among different variables of the electricity trading (Skantze and Ilic, 2001). Researchers have also come up with different simulation based pricing models (Skantze and Ilic, 2001).

The deregulation and resulting market competition have helped to increase the interest among research community to explore the issues related to the electricity spot prices modeling. However, the number of publications that address the issue of modeling and or forecasting electricity prices have been relatively small when compared to studies that target other commodities. There are several reasons for this. The methodologies traditionally employed to model the behavior of the stock prices and the price of other commodity products may not apply to electricity because of the non-storability of the electricity. The fact that electricity cannot be stored in meaningful quantities makes it impossible for the LSEs to create an arbitrage opportunity using inventory of electricity and exploiting the spot price process. The market maturity may be another reason. Many of the electricity markets are relatively young and are still developing.

The publications that investigate the modeling of electricity spot prices using time series methods mostly investigate the univariate modeling of a single series of spot prices. An exception is de Vany and Walls (1999) who introduced the concept of co-integration and convergence of electricity markets. In simple terms, co-integration means that a set of time series exhibits similar non-stationary behavior over the long run. Such co-integration can occur when all the components of a multivariate time series are correlated to an observed or unobserved component series that has a unit root.

Among the studies that employed univariate modeling, Knittel and Roberts (2001) utilized simple time series modeling techniques to analyze California market price data. Escribano, Peña, and Villapana (2002) proposed a relatively general modeling technique for electricity prices, and applied it to four different markets. Cuaresmaa et al. (2004) used univariate time series models to forecast the high frequency electricity spot-prices. The results indicated a strong overlapping seasonal behavior. According to Cuaresmaa et al. (2004), electricity spot-prices follow superposed seasonal cycles, and have properties of mean reversion and price spikes. Gibson and Schwartz (1990) and Brennan (1991) also support mean reversion property of electricity price. However, it is not a simple random walk (Carnero et al., 2004). Escribano, Peña, and Villaplana (2002) present salient features of electricity prices such as seasonality, mean-reversion, and jumps and volatility. Although such properties of the electricity spot price processes may shift the model towards a non-linear type of analysis, Cuaresmaa et al. (2004) concentrates only on linear univariate models. It helps to keep the model parsimonious. However, as Cuaresmaa et al. (2004) points out, non-linear time series analysis can provides very helpful and interesting framework to understand the price movements. Robinson develops a non-linear time series model for non storable commodities like electricity. Both of the above studies use ARMA models and include unobserved components and jumps in their study to forecast the electricity spot prices using hourly data.

Price spike can be observed in the market which can be attributed by the supply sided of the equation such as unplanned outage of a particular power plant in the market footprint or heavy congestion in the transmission line or even a transmission line trip off (Cuaresmaa et al., 2004). The price spikes can also be explained by the demand side of the equation. For example, extreme warm summer could cause more demand for power causing sudden spikes for the demand of electricity. In the competitive electricity market, it will most likely shoot the price up therefore causing a spike. However, it is important to note that the ISOs have cap on how much the price could spike up for a given hour. NYISO, MISO, ISO-NE and PJM capped the hourly spot market price bids at $1000/MWh.

Cuaresmaa et al. (2004) shows that the price jumps are mostly during the peak hours (peak hours are defined as the time period starting with 0800 hrs till 2300 hrs, Monday through Friday except holidays). Our analysis confirms their findings.

As Gibson and Schwartz (1990), Brennan (1991), Cuaresmaa et al. (2004) and Knittel and Roberts (2001) point out, the standard model for mean reverting processes is simple first order autoregressive process [AR(1)], which is a discrete time representation of an Ohrstein–Uhlenbeck process. Structural time-series models such as the unobserved components model (UCM) are popular in econometric studies and these models are developed to identify the unobserved components that drive the process. Characteristics of such components can be directly extracted from the data (Harvey and, Jaeger, 1999; Harvey, 1989; Harvey, 1985; Harvey, 1993). UCM helps to decompose the time series of interest into different components namely a trend component, cyclical components, seasonal components and an irregular component, in an additive fashion. Each of the components models different aspect of the behavior of the time series. Cuaresmaa et al. (2004) defines the cyclical component in a sine–cosine wave form with constant frequency, and models the seasonal component using seasonal dummies. The authors model the irregular component as white noise.

Other contributions on electricity spot price analysis and modeling are studies by Knittel and Roberts (2001), Lucia and Schwartz (2002), Escribano et al. (2002), and Wilkinson and Winsen (2002). Unlike the above contributors, Carnero et al. (2004) presents a model to investigate in the conditional mean and in the volatility of the innovations of the electricity spot pricing process. They argue that mean and variance of electricity spot prices do not only depend on the day of the week, but also on skewness, kurtosis and autocorrelation between hourly prices. Their argument involves around European market and for these markets, the variance of innovations depends on the specification for the conditional mean. Based on this aforementioned finding, they claim that the previous empirical studies on price volatility may have produced spurious results.

Another approach is to model the hourly price separately for each hour. Huisman, Huurman and Mahieu (2007) discuss a panel method approach for DA hourly electricity prices. The authors divide hourly prices as a panel of collection for that hour and create 24 cross-sectional panels. Each panel data set represents the hourly price data for that node for a particular hour. This paper proposes a panel model for DA hourly electricity prices in which the authors describe the dynamics of hourly cross section over time. However this model may fail to capture the autocorrelation between hourly prices lagged by, say, one hour. The daily average price (peak, off peak or overall) for electricity can be significantly different from the actual hourly prices and therefore, the forecasting models developed for average prices cannot be applied to forecast the hourly price Huisman, Huurman and Mahieu (2007). The issue is even more complicated as the electricity price follows mean reversion property. Also, there is no guarantee that the mean reversion rate would be constant for every hour or every season or week. The electricity price depends a lot on unit availability, weather, transmission constraints and demand for energy. And such properties can change every hour. Therefore, a daily average model will not work to forecast the hourly price.

As mentioned by Eyedeland and Wolyniec (2003) a good price forecasting model should be able to assimilate price spikes (kurtosis), mean reversion, fat tails of the price distribution and seasonality component. The model should also a include volatility surface, correlation structure between different forward contracts and cross commodity correlation between different commodities.

Although load profile seems to follow certain shape depending on different calendar effects, there is no single quick methodology to forecast the price. Part of the reason is that the physical properties of the locational marginal price vary from market to market (Smith, 2000). The electricity pricing is coupled with the fundamental differences in different markets, different generation types, volatility structure and regulations. The nonstorablity of the electricity makes it harder follow a particular path. Also availability of financial instruments makes modeling more market centric. For example, let us consider virtuals. One of the objectives of this dissertation is to investigate if the virtuals can cause a price convergence or divergence. But virtuals may not be offered in all electricity markets in US. PJM & ISO-NE were among first few to introduce this instrument. The MISO was third to introduce virtuals.

One of the major characteristics of electricity market is the possibility of negative LMPs. It is a unique characteristic of electricity price. Nevertheless, we could find only one paper which addresses the issue of negative LMP; unfortunately, the authors did not address the issue in depth (Sewalt and De Jong, 2003). This crates problem if one tries to model the price data by normalizing the price with natural logarithm. Also since negative LMPs do not occur in a pattern, it is difficult if not impossible to model such data.

There is evidence that the DA electricity price has a high correlation with the gas price observed in the gas market (Eydeland and Wolyniec, 2003). Also, publications by Smith (2000), Harvey (1989) and Bartels and Fiebig (2000) have pointed that, hourly price has a strong relationship with the load pattern. Figure 4.1 proves such claims.

There are other factors that could affect the electricity price. For example, let us consider a day in summer in which the temperature is expected to be really high. This indicates that there would be a higher demand and that will probably increase the price of the electricity. Let us assume that there is a forecast of thunderstorm with higher probability in the evening. If the temperature remains high and there is thunderstorm, then the general expectation is that the price will remain high. However, if the thunderstorm occurs, then the expectation is that the demand for load will drop and therefore the price should also drop. A power trader will keep this information which is different for both morning and evening in mind and set his trade price with this rational expectation. With this example it is clear how information set could change from hour to hour and therefore, could change rational expectation of market price.

4.2. ELECTRICITY PRICE VOLATILITY MODELING

In a typical commodity market such as corn or oil or gold, where the underlying asset can be stored, price fluctuation due to the demand and supply can be lessened by surplus storage. However, since electricity is non-storable commodity, sudden increase in the system load must be satisfied either through instant production or buying from another generator which may have surplus generation capability. This could spike up the price instantly. Also, if there is any congestion or transmission outages in a particular line, then market will react with a higher price. Such phenomenon in the electricity market cause short-term volatility in the price. The volatility can exist for hours, days before it returns to the normal price level. Other factors such as availability of generation fuels can also affect the price volatility. So, in the context of the electricity price modeling, one must discuss the volatility associated with the electricity price. The fitted model must be able to capture the volatility observed in the market. The following section briefly discusses some of the volatility models widely used in the electricity market.

4.2.1. Constant Volatility Models. In simple term one can compute historical standard deviation using standard statistical formulation of the standard deviation of lognormal electricity price. If option price data is available, then one can find constant volatility in the Black-Scholes frame-work by expressing volatility as a function of option price, exercise price, time to expire, interest rate and underlying price (Duffie, Gray and Hoang, 1999). However, this process requires employing numerical methods such as Newton-Raphson method to solve for the unknown variable. Although Black-Scholes world requires constant volatility as an input to the pricing model, Duffie, Gray and Hoang (1999) explains how it can still be used to forecast the volatility. It is possible as option price reflects the true nature of the market uncertainty and risk premium.

4.2.2. Stochastic Volatility Models. GARCH models are widely used to forecast the price volatility (Hadsell and Shawky, 2006). Guirguis and Felder (2004, 2005) presents GARCH (1,1) model to forecast the volatility in the electricity price models. Their model also incorporates natural gas prices of the previous period (lag one data), which is not surprising as the gas and power market generally has a strong correlation. The problem with the GARCH or any other time series based models is that it usually takes the natural logarithm of the price to process the data. However, since electricity price can be negative or zero, such models will not be able to process the data. Alvarado and Rajaraman (1998) consider a Wiener process and mean reversion process to characterize the price volatility. Hadsell and Shawky (2006) also use GARCH model to estimate volatility in wholesale electricity prices observed in both the DA and RT markets. They study marginal cost of congestion and DA premium and show how these variables impact price volatility. Li and Li-zi (2008) also used GARCH based model to forecast the volatility and price. Hadsell and Shawky (2006) found that the price volatility is higher but less persistent in the RT market than in the DA market. They also consider the importance of transmission congestion in the price volatility and empirically estimate impact of congestion on volatility observed in electricity prices. Borenstein et al. (2002), support their theory to include the congestion etc. by arguing that the main reasons for the observed price behavior are inelastic demand, non-storability of electricity, and congestion. Hadsell, Marathe and Shawky (2004) study five different U.S. markets and estimate conditional volatility that exists in those markets. They show that that the deregulated markets usually exhibit higher level of price volatility compared to other traditional commodity markets. Further research asserts the importance of congestion in determining prices. Isabel and Soares (2005) also use GARCH based model to study the volatility observed in the spot prices in Spanish electricity market. There are several other publications where researchers used other methods such as TGARCH, regime-switching model etc. to develop the volatility model.

While historical volatility helps us to understand how the market behaved in the past, it is also important to have the price models that correctly capture the volatility arising from other commodity markets such as natural gas or oil. However, most of the analysis reviewed so far in this dissertation are based on the historical data and therefore, gives a good judgment on the historical volatility. This merely gives enough information on how the future movement will be, especially in electricity market that is quite different from other traditional financial market. A good measure of the forward volatility is probably the implied volatility extracted from the market quoted option prices (Eydeland and Wolyniec, 2003). Expressing the market quoted option value as a function of quoted forward price, expiration time, volatility and interest rate one can solve the equation for the volatility using numerical methods such as Newton's method. Volatility extracted from the market quoted price information reflects the true market sentiment about the forward price volatility.

4.3. FORWARD ELECTRICITY MARKET

There exists several forward market products that are structured based on time of the day (peak/off peak hours), day of the week, weekday or weekend etc. Most of them are traded over the counter on a platform called ICE[5]. ICE also works as clearing organization. Although the forward electricity price does not converge to the actual observed spot price, it may be possible for someone to find an empirical relationship between the forward market and the DA market price. Literature (Shawky, Marathe and Barrett, 2003; Longstaff and Wang, 2004) related to the forward and spot market price try to express the forward price by capturing the risk premia that exists between the spot price and forward market. We are not sure if the same can be reversed (by expressing spot price as a function of forward price). There may be other explanatory variables that will explain the reverse relationship.

There are two main challenges in forward price modeling for electricity price process—nonstorablity of electricity (and therefore typical risk neutral method cannot be

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[5] Intercontinental Exchange or ICE is the trading place for most of the OTC products in the power market. The market participants in the ICE platform include some of the large global trading organization to small utility companies.

applied) and basis risk. Models that try to provide prices of the individual contracts are most likely to fail to capture the right phenomenon as the cash flow from a particular derivate does not depend just on one futures, but also on the term structure of the forward prices at a given time. Many models have been developed with this approach based on HJM (Heath, Jarrow and Morton, 1992) interest rate model (Eydeland and Wolyniec, 2003). Nevertheless, these models also do not capture the non-convergence of the forward and spot market power price. Also, the risk neutral approach is not well suited in the power market. Some of the interesting papers, which explain the relationship between spot price and futures to quantify the basis risk, are discussed below. The quantification of the specific parameters of these models are not discussed in this dissertation as they would change based on the test market. However, we believe that the same model or a similar model can be fitted to other electricity markets.

The two factor model proposed by Schwartz-Smith (2000) attempts to capture some dynamics from the spot market by adding a risk premium. It's important to note that the model is still formulated in the risk neutral world. In this model, the forward price process is linked to spot price process through two different random variables—one shows the long term behavior of the spot price process whereas the other one captures the short term behavior. The formulation provided by Schwartz-Smith (2000) shows the necessary price evolution and interaction between the spot price and the forward price. However, it sometimes fails to capture the initial forward curve (Eydeland and Wolyniec, 2003). Also, since the model parameters are estimated using the data which may exhibit negative spot price, lognormal assumption may be troublesome at times.

Hadsell, Marathe, Barrett (2004) fits a GARCH based model to present the empirical relationship between the futures price and spot price in electricity market. Longstaff and Wang (2004) author another paper that tries to model the forward price based on the difference that exists between the forward and spot markets. Their model is based on the PJM spot and forward market data. The authors present a formulation for the expected premium based on a time series model where they have an expected local and conditional volatility (GARCH) variable.

Based on the above discussions, price forecast models can be classified into several types—some based on fundamentals and some based on temporal relationships between the market dynamics and load. No matter what approach is followed, the RT LMP is always the hard nut to crack. This is because of the uncertainty observed in the RT Market arising from weather and physical properties of distribution systems. These uncertainties are difficult to forecast. In this dissertation, the second approach has been followed.

5. HEDGING AND SPECULATION USING VIRTUALS

5.1. RISKS AND RISK MANAGEMENT

As discussed in the Sections 3 and 4, load and price depend on many variables including weather, unit outage, congestion, transmission line problems etc. Each of these could cause significantly on a market participant. The risks can be classified in to two key categories—volumetric and price risks. Figure 5.1 shows how these risks affect the market participants for any given hour. Let us assume a hypothetical generation company that also serves load. Lets consider that the Genco/LSE serve approximately 500MW to its native load (NL).

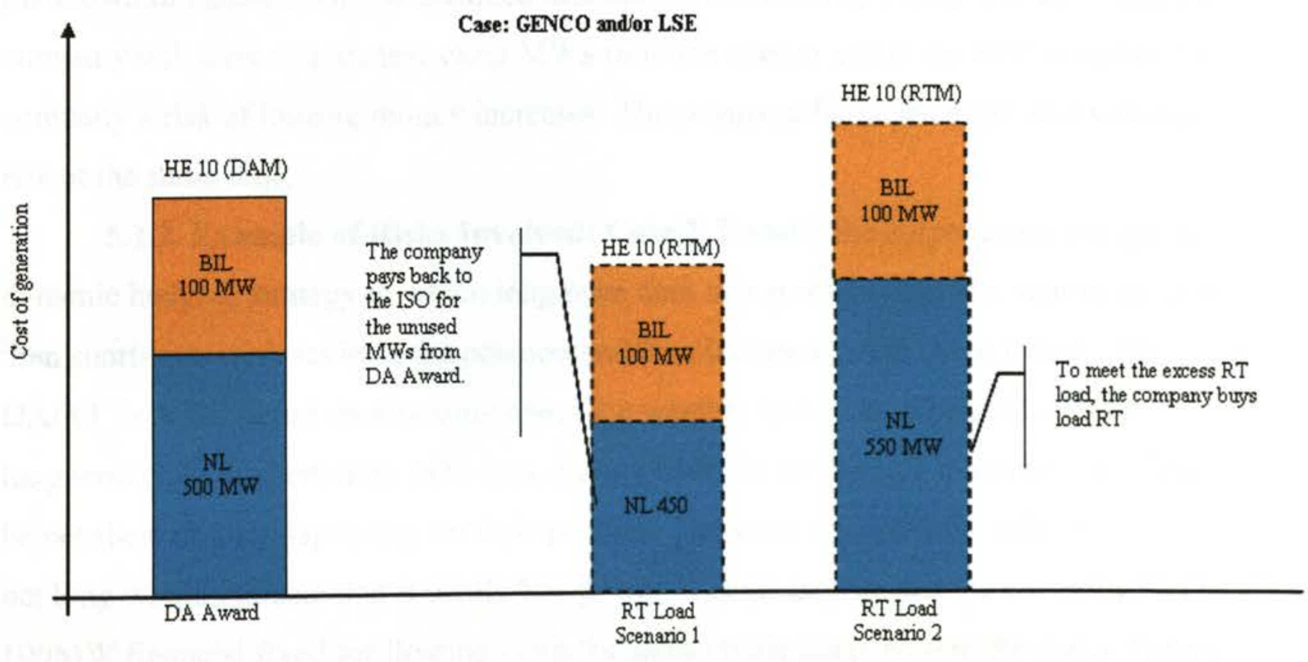

Figure 5.1. Price and Volume Risks

To make it more realistic, it is assumed that the company has another 100MWs of commitment from a physical bilateral agreement that it intends to serve from its own generation resource. Let us assume that the company participates in the DA market associated with a certain ISO and it receives DA award for HE 10 as shown in Figures 5.1 and 5.2. If it does not receive any generation award in DA market (which means the company can purchase electricity at a cheaper rate than it offered to sell at DA market), then it must purchase the electricity in the RT market. With the DA award, the company is guaranteed an amount at the rate of DA LMP for the awarded MWs. Let us assume that it receives 600MW as DA award.

5.1.1. Example of Risks Involved: Case 1. In RT the company can face several situations. In Scenario 1 (Figure 5.1), it is assumed that the NL drops to 450MW. This means that the company must return the 50MW that it did not produce in RT at RTP to the ISO. If the RTP is lower than DAP, then the company would make money. However, if the RTP is higher than the DAP, then the company would loose money. In Scenario 2 (as shown in Figure 5.1), it is assumed that the NL increases by 50MW. In this case, the company will have to purchase extra MWs from the market and if the RTP is higher, the company's risk of loosing money increases. The company faces price risk and volume risk at the same time.

5.1.2. Example of Risks Involved: Case 2. Usually the corporations engage in dynamic hedging strategy in which long term desk sets position almost a year in advance, then short-term desk reviews the position and then it comes to the DA/RT desk. The DA/RT desk has better understating about the weather and other physical factors which long term (LT) or short-term (ST) desk did not have. In the DA/RT market, it can either be net short or long depending on their position. Net short would be net sales position and net long would indicate that it would buy power. Let us assume that the company has 100MW financial fixed for floating swap (bilateral) trade made by one the desks. Figure 5.2 explains the Case 2.

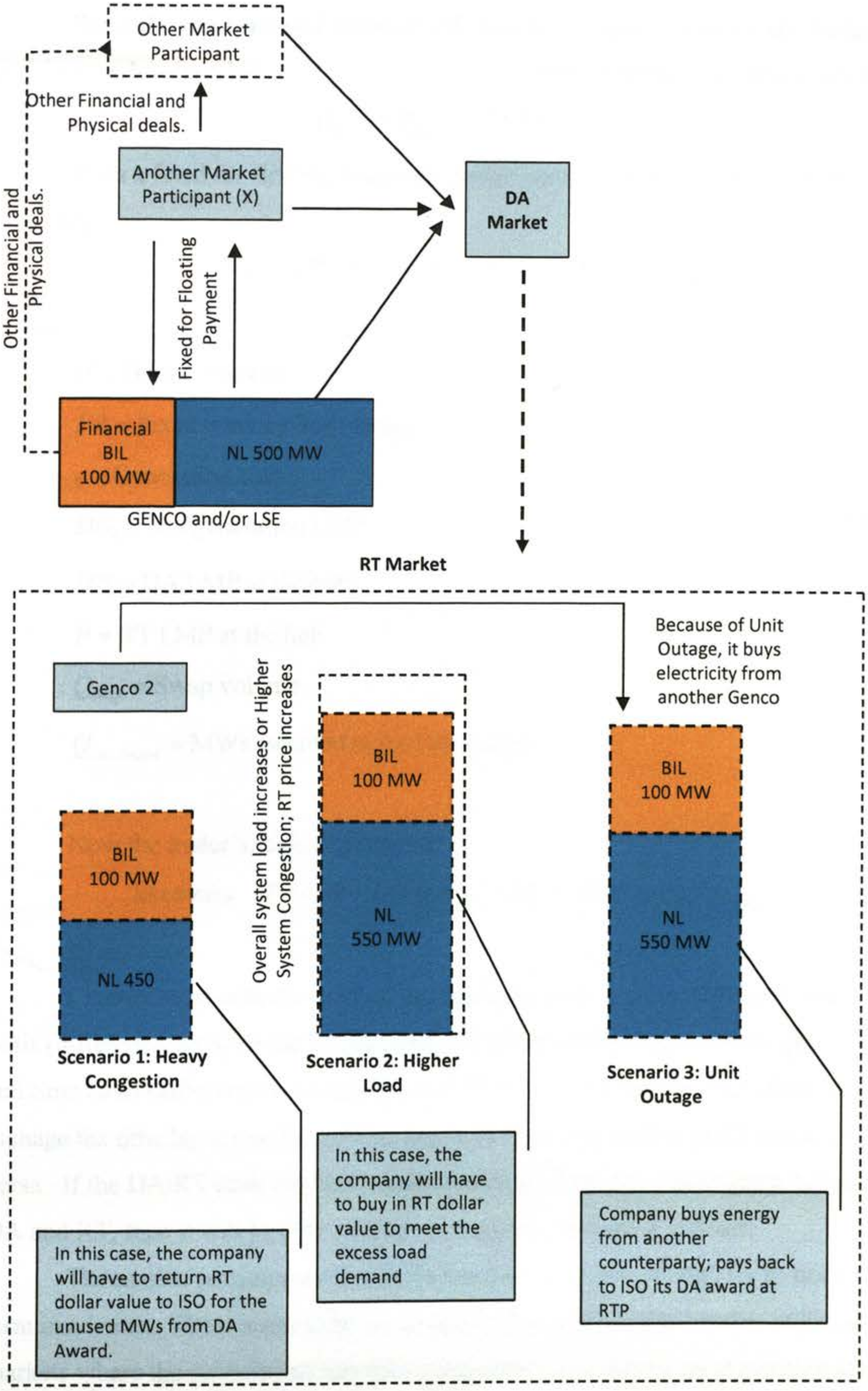

Figure 5.2. Risk and Hedge in DA/RT Market Scenario

Since the company had received DA awards, its margin without any hedge position can be given by:

$$\Pi_{w/o} = Q_{DA\,Award} * DG_t - c. \quad (1)$$

With a fixed for floating hedge the hedge margin equation changes to the following

$$\Pi = (FR - c) + ((DG_t - DP_t) + (DP_t - P)) * Q_{swap} \quad (2)$$

Where,

Π = Hedge margin

FR = Fixed revenue from swaps

c = Generation cost

DG_t = DA generation LMP

DP_t = DA LMP at the hub

P = RT LMP at the hub

Q_{swap} = Swap volume

$Q_{DA\,Award}$ = MWs awarded in the DA market.

Now the trader's main objective is

$$Maximize \;\; \Pi = (FR - c) + ((DG_t - DP_t) + (DP_t - P)) * Q_{swap}. \quad (3)$$

Clearly, even with the hedges, the company now face two different risk—location basis (difference between the LMPs observed in two nodes—hub and the generation unit) and time basis (difference between DA and RT price). Virtual bid and offers help to manage the time basis risk by moving exposure from DA market to RT market or vice versa. If the DA/RT desk has better understanding of the price divergence between the DA and RT, then it will be able to better manage the risk using virtuals.

The market participants face different risks even though they try to hedge long-term in advance. There seem to be no perfect hedge in electricity market unlike other markets where the participants can take consecutive long and/or short position along with the position on derivative products on the same underlying to create a perfect hedge. This happens because of some unique properties of electricity discussed in earlier chapters. Organized markets such as MISO or PJM gives an opportunity to its participants to better manage their risk using a financial instrument called virtuals. Virtuals (offer and bid) are purely financial tools which allow the market participants to hedge the DA/RT risk by offering or bidding for "virtual megawatts or generation" in the market. If a market participant is awarded certain amount of virtual bids in the DA market, those awarded virtual MWs would be sold back to the RT market at the RT LMP at that CPNode where the original bid was submitted and subsequently cleared. Virtual offers act in opposite direction. The virtual offers or supply cleared in the DA market are bought back from RT market at RT LMP observed at that CPNode where the original offer was submitted and subsequently cleared. Clearly, the payoff for the market participants is the difference between the DA and RT LMP at the respective CPNode for the MWs the participant was awarded.

5.2. VIRTUAL BIDS AND OFFERS

Virtual trading is "somewhat" similar to futures trading in traditional commodity markets. Similar to futures market, the virtual trading market can also be divided into two groups—hedgers and speculators. The objective of the "Hedgers" is to protect their position in electricity market from price variations in DA/RT market and on the other hand, speculators try to make arbitrage profit by guessing market moves and buying or selling a commodity without any physical presence for which they have no practical use. However, the difference between the "virtual" and "futures" contract is manifold. The primary difference is in the market mechanism in which they settle. The futures market trade many months before the actual delivery date where as one can bid or offer the virtual trade on the seven days prior to the operating day (in MISO). Every market has its own rule on how virtuals be traded and cleared. Forward market works almost in same mechanism in every market in the US. Also, a major difference with the forward market is that all submitted bids and offers may not be cleared. The virtuals are always cleared in DA market. The mechanism of the cleared virtuals in the DA market is such that it automatically creates a position that would be reversed in RT market.

Virtuals were introduced in the market with the intent of bringing more liquidity and provide another hedging tool to the participants. It was first introduced in US in PJM on Jun 1, 2000. NYISO subsequently introduced virtuals as a trading instrument November 8, 2001. New England (ISO-NE) introduced in March 1, 2003 and MISO on April 1, 2005. Although some literature on market design have indicated virtuals, there are only a few publications that deal with the virtual in depth. In addition, we did not find any comprehensive literature that identifies how different trading strategies can be implemented using virtuals. Dr. Peter Cramton testified that virtual trading could help in increasing efficiency in the response time for both the supply and demand in the real-time market[6]. According to his testimony, it can reduce price volatility, improve market competition, and ultimately increase market liquidity, which was a big concern at the onset of power market trading and deregulation. Different market monitors (Isemonger and Rahimi, 2006) have endorsed Dr. Cramton's opinion.

The market participants do not need to be backed by physical generation units and that is why it is called virtual. However, the virtual bids or offers must be submitted for a particular Commercial Pricing Node or CP Node (generation node, load zone/node, interface node, or hub) in the footprint of that particular market clearing authority. The participants submit their bids and offer which are purely financial to the market clearing authority (such as ISO). The market clearing authority stack the orders on top of the physical demand bids and offers before it clears the DA/RT awards. The price for the cleared virtual bids or offers is the Locational Marginal Price (LMP) of the where the virtual bid or offer was submitted. Clearly, the traders make their bids and offers based on their speculation over the DA and RT prices.

There is no counterparty involved in the virtual transaction and therefore the market participant assumes all the risks involved with its transaction. This is another major difference with the forward market. However, the ISO may require the participant to deposit collateral with ISO to ensure protection against risk arising from future non payment during the settlement. The ISO usually has a credit limit for each individual participant that may limit its trading limit for the virtual. The ISO may also have a

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[6] See Isemonger and Rahimi, 2006

general cap on the amount of virtual bids or offers a market participant can submit. This limit may vary for one ISO to another.

The instrument essentially helps the market participants hedge their market position or exposure by moving their DA/RT exposure either way depending on their judgment. The virtual market attracts many financial organizations and therefore bringing much liquidity to the market (Saravia, 2003)[7].

From the market structure, it is clear that financial speculators can influence the DA/RT price difference (Saravia, 2003). Saravia (2003) indicates two important reasons—i) speculators or financial participants help market to be more liquid and efficient and ii) by participating in the market, they assume some of the market risk which should decrease risk premium that exists between DA/RT market. Since virtual bids and offers are included in the DA stacking, they can increase or decrease LMP at certain nodes. Clearly, there is no distinction between virtual and physical bids in the DA market. However, since the cleared participants will have to reverse the position in the RT market, they would have all the incentive the influence the market in their favor.

Saravia (2003) indicates that the DA LMP cannot be an unbiased estimator or forecast of the RT price. If this were true then in a market (for virtual) where there is no transaction costs associated with the trades, speculative risks should not have been correlated with the overall market risk. This infers that that virtual demand and supply patterns along with DA LMP and other factors can give well indication of the RT price movements.

Saravia (2003) also indicates how gaming can be done in the electricity market in the absence of the speculative traders. Generators in the exporting zone can withhold sales in the exporting zone so that the DA market will be uncongested for that particular line. In the RT market, the generators can actually increase the generation which will increase the congestion amount more than what was in the DA market and therefore would raise the LMP in that node. The opposite is also possible. The generator can over schedule a particular transmission line and therefore the congestion would increase in that line. However, in the RT, the load will be lower and therefore less congestion and lower

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[7] Also refer to MISO Business Practice Manual from http://www.midwestmarket.org/publish

LMP. With lower LMP, the generator can purchase electricity from the market and make arbitrage profit. Similarly, it is possible to game the market using the Congestion Revenue Rights virtuals and the virtuals[8]

No hedge will probably bring zero risk, especially in the electricity market. The generation companies try to hedge based on long term, short term and then on a DA/RT basis. The climate forecasts can (and will) change since when the long term or short-term deals are entered. Therefore, it is left to the DA desk to shift the LT or ST hedges as needed based on the updated weather forecast. However, in RT market the participants may incur losses based on the sudden line or plat tip off or higher congestion on certain lines or even with higher or lower consumption of electricity. Also, credit risk or counter party risk has been emerging as an important factor in the risk management process. For example, let's consider the case of Bear Energy. Although people anticipated Bear Stern (the parent company of Bear Energy) to incur huge losses from mortgage crisis, very few if not none expected them to suddenly face severe liquidity crisis which resulted in selling itself at a very low price. Many power-trading companies which had Bear Energy as counterparty may have to forego any profit if the company declares bankruptcy. Clearly, even if a trading or electricity marketing or producing company is optimally hedged against possible volume and price fluctuation, it may not actually have a zero risk at all.

5.3. TRADING STRATEGIES INVOLVING VIRTUALS

In this section, different speculative and hedging strategies involving virtual bids and offers are discussed. The strategies are described with specific situation in mind. In this example, a hypothetical Genco, which has approximately 500MWs load commitment for a particular hour is considered. In this case, the following assumptions are made:

- The Genco does not have position in any other financial or physical instrument to hedge their risk.
- The Genco's offer for 500MW generation is cleared in DA market.
- The DA LMP for that particular hour is $100/MW.

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[8] Oren, S.,"The Nordic Electricity Market", Presented at the 23rd Arne Ryde Symposium, Lund, Sweden,

- The virtual bid or offer amount shown in the example is also cleared in DA market. All the cleared virtuals are on the same CPNode.

Tables 5.1, 5.2, 5.3 and 5.4 show different strategies involving virtuals and the payoff structures associated with those strategies.

5.3.1. Position and Strategy: Case 1. Genco has a long position. The Genco has been awarded a 50MW Virtual bid which also clears at $100/MW. Tables 5.1 discusses trading related to Case 1.

Table 5.1. Strategies Using Virtuals and Payoff Structures: Case 1

Situations	Payoff
1. RT LMP > DA LMP and RT load does not change. RT LMP is $110/MW.	1. DA Awards = 500MW *$100/MW = $50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($110-$100/MW) = $500 Therefore, net benefit = $55,000- Cost of Production.
2. RT LMP < DA LMP and RT load does not change. RT LMP is $90/MW.	2. DA Awards = 500MW *$100/MW = $50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($90-$100/MW) = -$500 Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 500MW in RT = $45,000. Therefore, net benefit = $50,000-45,000 - 500 = $4500.

October 2003; We reference: www.nek.lu.se/ryde/23symp03/Papers/oren.ppt (Last visited: 20 June 2008)

Table 5.1 (Continued). Strategies Using Virtuals and Payoff Structures: Case 1

Situations	**Payoff**
3. RT LMP > DA LMP and RT load increases 20 MW. RT LMP is \$110/MW.	3. DA Awards = 500MW *\$100/MW = \$50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (\$110-\$100/MW) = \$500 However, the company buys 20MW in RT at RT LMP. Cost of RT purchase = 20MW* \$110/MWh = \$2200. Therefore, net benefit = \$50,500- 2200 - Cost of Production. = \$48,300 - Cost of Production
4. RT LMP <DA LMP and RT load increases 20 MW. RT LMP is \$90/MW.	4. DA Awards = 500MW *\$100/MW = \$50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (\$90-\$100/MW) = -\$500 Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 520MW in RT = \$46,800. Therefore, net benefit = \$50,000-46,800- 500 = \$2,700.
5. RT LMP > DA LMP and RT load decreases 20 MW. RT LMP is \$110/MW.	5. DA Awards = 500MW *\$100/MW = \$50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (\$110-\$100/MW) = \$500 However, the company has to pay back to the ISO for 20MW that it did not produce because of decreased load. It pays RT LMP. Loss due to this = 20MW* \$110/MWh = \$2200. Therefore, net benefit = \$50,500- 2200 - Cost of Production =\$48,300 - Cost of Production

Table 5.1 (Continued). Strategies Using Virtuals and Payoff Structures: Case 1

Situations	Payoff
6. RT LMP <DA LMP and RT load decreases 20 MW. RT LMP is $90/MW.	6. DA Awards = 500MW *$100/MW = $50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($90-$100/MW) = -$500 Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 480MW in RT = $43,200. However, the company has to pay back to the ISO for 20MW that it did not produce because of decreased load. It pays RT LMP. Loss due to this = 20MW* $90/MWh = $1800. Therefore, net benefit = $50,000-43,200- 500 -1800= $4,500.

5.3.2. Position and Strategy: Case 2. Genco has a long position. The Genco has been awarded a 50MW virtual offer. The virtual offer clears at $100/MWh. Tables 5.2 discusses the trading strategies and payoffs involving Case 2.

Table 5.2. Strategies Using Virtuals and Payoff Structures: Case 2

Situations	Payoff
1. RT LMP > DA LMP and RT load does not change. RT LMP is $110/MW.	1. DA Awards = 500MW *$100/MW = $50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (-$110+$100/MW) = -$500 Therefore, net benefit = $49,500- Cost of Production.

Table 5.2 (Continued). Strategies Using Virtuals and Payoff Structures: Case 2

Situations	Payoff
2. RT LMP < DA LMP and RT load does not change. RT LMP is $90/MW.	2. DA Awards = 500MW *$100/MW = $50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (-$90+$100/MW) = $500 Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 500MW in RT = $45,000. Therefore, net benefit = $50,000-45,000 + 500 = $5500.
3. RT LMP > DA LMP and RT load increases 20 MW. RT LMP is $110/MW.	3. DA Awards = 500MW *$100/MW = $50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (-$110+$100/MW) = -$500 However, the company buys 20MW in RT at RT LMP. Cost of RT purchase = 20MW* $110/MWh = $2200. Therefore, net benefit = $49,500- 2200 - Cost of Production. = $47,300 - Cost of Production
4. RT LMP <DA LMP and RT load increases 20 MW. RT LMP is $90/MW.	4. DA Awards = 500MW *$100/MW = $50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (-$90+$100/MW) = $500 Since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 520MW in RT = $46,800. Therefore, net benefit = $50,000-46,800 + 500 = $3,700.

Table 5.2 (Continued). Strategies Using Virtuals and Payoff Structures: Case 2

Situations	Payoff
5. RT LMP > DA LMP and RT load decreases 20 MW. RT LMP is \$110/MW.	5. DA Awards = 500MW *\$100/MW = \$50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (-\$110 +\$100/MW) =- \$500 However, the company has to pay back to the ISO for 20MW that it did not produce because of decreased load. It pays RT LMP. Loss due to this = 20MW* \$110/MWh = \$2200. Therefore, net benefit = \$49,500- 2200 - Cost of Production =\$47,300 - Cost of Production
6. RT LMP <DA LMP and RT load decreases 20 MW. RT LMP is \$90/MW.	6. DA Awards = 500MW *\$100/MW = \$50,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (-\$90 +\$100/MW) = \$500 Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 480MW in RT = \$43,200. However, the company has to pay back to the ISO for 20MW that it did not produce because of decreased load. It pays RT LMP. Loss due to this = 20MW* \$90/MWh = \$1800. Therefore, net benefit = \$50,000-43,200+ 500 -1800= \$5,500.

5.3.3. Position and Strategy: Case 3. Genco has a short position of 10MW. Let's assume that the company was awarded 490MW in DA Market. The Genco has been awarded a 100MW virtual bid with a DA price of $100/MW. Table 5.3 discusses the trading strategies and payoffs involving Case 3.

Table 5.3. Strategies Using Virtuals and Payoff Structures: Case 3

Situations	Payoff
1. RT LMP > DA LMP and RT load does not change. RT LMP is $110/MW.	1. DA Awards = 490MW *$100/MW = $49,000 It buys 10MW in RT. So, cost for 10MW = 10 MW*$110/MW = $1100 In RT, the virtuals are converted. Proceeds from virtuals =100MW * ($110-$100/MW) = $1000 Therefore, net benefit = $49,000- 1100 +1000 -Cost of Production =$48,900 -Cost of Production.
2. RT LMP < DA LMP and RT load does not change. RT LMP is $90/MW.	2. DA Awards = 490MW *$100/MW = $49,000 It buys 10MW in RT. So, cost for 10MW = 10 MW*$90/MW = $900 In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($90-$100/MW) = -$500 Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 490MW in RT = $44,100. Therefore, net benefit = $50,000-44,100 - 500 -900= $4500.
3. RT LMP > DA LMP and RT load increases 20 MW. RT LMP is $110/MW.	3. DA Awards = 490MW *$100/MW = $49,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($110-$100/MW) = $500

Table 5.3 (Continued). Strategies Using Virtuals and Payoff Structures: Case 3

Situations	Payoff
	The company buys 20MW in RT at RT LMP to serve the load. Since the company is short, it needs to buy 10 MW in the RT market. The cost = 30MW* $110/MWh = $3300 Therefore, net benefit = $49,500- 3300 - Cost of Production. = $46,700 - Cost of Production
4. RT LMP <DA LMP and RT load increases 20 MW. RT LMP is $90/MW.	4. DA Awards = 490MW *$100/MW = $49, 000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($90-$100/MW) = -$500 Since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 520MW in RT = $46,800. Therefore, net benefit = $49, 000-46,800- 500 = $1,700.
5. RT LMP > DA LMP and RT load decreases 20 MW. RT LMP is $110/MW.	5. DA Awards = 490MW *$100/MW = $49,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($110-$100/MW) = $500 However, the company has to pay back to the ISO for 10MW that it did not produce because of decreased load. It pays RT LMP. Loss due to this = 10MW* $110/MWh = $1100. Therefore, net benefit = $49,500- 1100 - Cost of Production =$48,400 - Cost of Production
6. RT LMP <DA LMP and RT load decreases 20 MW. RT LMP is $90/MW.	6. DA Awards = 490MW *$100/MW = $49,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($90 -$100/MW) = -$500

Table 5.3 (Continued). Strategies Using Virtuals and Payoff Structures: Case 3

Situations	Payoff
	Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 480MW in RT = \$43,200. However, the company has to pay back to the ISO for 10MW that it did not produce because of decreased load. It pays RT LMP. Loss due to this = 10MW* \$90/MWh = \$900. Therefore, net benefit = \$49,000-43,200- 500 -900= \$4,400.

5.3.4. Position and Strategy: Case 4. The Genco has a short position of 50MW. The company was awarded 450MW in DA Market. The Genco has also been awarded a 50MW Virtual bid at \$100/MW. Table 5.4 discusses the trading strategies and payoffs involving Case 4.

Table 5.4. Strategies Using Virtuals and Payoff Structures: Case 4

Situations	Payoff
1. RT LMP > DA LMP and RT load does not change. RT LMP is \$110/MW.	1. DA Awards = 450MW *\$100/MW = \$45,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (\$110-\$100/MW) = \$500 It also buys 50MW in RT. Cost associate with this =50*\$110=\$5500. Therefore, net benefit = \$45000+500-5500- Cost of Production =\$44,000- Cost of Production.
2. RT LMP < DA LMP and RT load does not change.	2. DA Awards = 450MW *\$100/MW = \$45,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (-\$90+\$100/MW) =- \$500

Table 5.4 (Continued). Strategies Using Virtuals and Payoff Structures: Case 4

Situations	Payoff
RT LMP is $90/MW.	Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 500MW in RT = $45,000. Therefore, net benefit = $45,000-45,000 - 500 =- $500.
3. RT LMP > DA LMP and RT load increases 20 MW. RT LMP is $110/MW.	3. DA Awards = 450MW *$100/MW = $45,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($110-$100/MW) = $500 However, the company buys 20MW in RT at RT LMP. It also needs to buy 50MW in RT. Cost of RT purchase = 70MW* $110/MWh = $7700. Therefore, net benefit = $45, 000- 7700 + 500 - Cost of Production. = $37,800 - Cost of Production
4. RT LMP <DA LMP and RT load increases 20 MW. RT LMP is $90/MW.	4. DA Awards = 450MW *$100/MW = $45,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($90-$100/MW) = -$500 Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 520MW in RT = $46,800. Therefore, net benefit = $45,000-46,800 -500 =- $23,00.
5. RT LMP > DA LMP and RT load decreases 20 MW. RT LMP is $110/MW.	5. DA Awards = 450MW *$100/MW = $45,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * ($110 -$100/MW) = $500 However, the company still needs to buy 30MW in RT. Loss due to this = 30MW* $110/MWh = $3300.

Table 5.4 (Continued). Strategies Using Virtuals and Payoff Structures: Case 4

Situations	Payoff
	Therefore, net benefit = \$45,500- 3300 - Cost of Production =\$42,200 - Cost of Production
6. RT LMP <DA LMP and RT load decreases 20 MW. RT LMP is \$90/MW.	6. DA Awards = 450MW *\$100/MW = \$45,000. In RT, the virtuals are converted. Proceeds from virtuals = 50MW * (\$90 -\$100/MW) =- \$500 Now since the RT LMP is lower than DA LMP, the company does not generate the electricity; it instead buys from market to serve the load. Cost to buy 480MW in RT = \$43,200. Therefore, net benefit = \$45,000-43,200+ 500= \$300.

Clearly the virtual strategy in Case 4 did not give as much as benefits as the trader may have thought. Clearly, a virtual bid strategy would have worked better in this situation. Table 5.5 summarizes different expected conditions and the virtual trading strategies the market participants may engage.

Table 5.5. Summary of Strategies Using Virtual Bid and Offers

Position	Forecasted Situation	Strategy
Net Long Position	RT LMP > DA LMP	Use Demand bid to secure the position in DA market and subsequently use virtual bid to convert the risk from RT Settlement to DA Settlement.

Table 5.5 (Continued). Summary of Strategies Using Virtual Bid and Offers

Position	Forecasted Situation	Strategy
Net Long Position	RT Load < DA demand and/or RT LMPs < DA LMP	Shift load price exposure from DA to RT with Virtual Offer. Buy the forecasted load with a demand bid, and use the virtual offer to sell back part of the load.
Net Long Position	RT Load > DA demand and/or RT LMPs < DA LMP	Use Virtual bid.
Net Short Position	RT LMP < DA LMP	Shift RT exposure to DA using virtual bid.
Net Short Position	Units trips off and is expected to return any time. However, we are not sure what time it may return to full capacity. A ramp up period may be necessary. DA LMP is expected to be lower than RT LMP.	Since we are not sure about the availability of the unit, it will be safer to limit the exposure to DA prices only using virtual bid. Offer generation in DA market and generator, but buy some back if the prices are low enough.
Net Short Position	Units trips off and is expected to return any time. However, we are not sure what time it may return to full capacity. A ramp up period may be necessary. DA LMP is expected to be higher than RT LMP.	Since the DA LMP is expected to be higher, the trader will take advantage using Virtual Offer. The strategy will be to offer the generation with a complementary virtual offer.

5.4. MARKET MANIPULATION USING VIRTUALS

The following section discusses one more trading strategy that can potentially manipulate the market. Please note that the market manipulation is illegal. This case has been discussed for study purpose only.

Consider the same Genco/LSE which was mentioned in the previous section. It is assumed that the company has a significant presence in the ISO it participates. It is further assumed that the Genco/LSE has a long position. The company significantly drops the demand bids in DA market, the over all demand for energy across the ISO would also drop. Then the Genco/LSE can make a full offer on its generation awards thus making the demand supply relationship settle for a lower DA price. Knowing this fact, the Genco/LSE in this example can put higher amount of virtual bids thus making money from the virtuals. The ISO would clear less generation offer as there was less demand for the energy in DA market. However, in RT, the load would come stronger compared to the DA market (or in other words, to the original level). With higher load than the DAD, the RT price would also come stronger. Now with higher load, the ISO will have to RAC some units, which were not cleared in DAM. The RAC will increase possibility for the Genco/LSE to earn revenue from make-whole payment scheme. Alternatively, the Genco/LSE can now increase its RTP to serve any extra MWs. The company will be able to perfectly manipulate the market and make money if there was no RSG fee. However, the RSG fee is distributed among all the market participants. There is also higher possibility of congestion related issues in RT market as the transmission lines were originally planned for lesser MWs in DAM. The congestion related issues can also be hedged using the FTR or CRR etc. So, there still exists a good possibility that a market participant with significant capacity will be able to manipulate the market prices.

6. UNOBSERVED COMPONENT MODELS AND GARCH MODELS

As discussed in the previous sections, electricity demand and load follow certain cyclical and seasonal patterns, which must be captured by the model. The long-term demand for energy also increases over long term due to economic growth and people's life style changes. Such change, however, may not be observed in the short term. The seasonal and cyclical nature of the electricity data has a direct interpretation of the load shape. Clearly, the load models should capture the cyclical and seasonal changes in the observed data. The main challenge is to model the seasonal and cyclical components of the demand and load data not as deterministic entities but as possess with stochastically changing patterns. The impact of weather and other variables must also be taken into account. This motivates us to consider Unobserved Component Model (UCM) to fit the load and demand datasets.

6.1. UNOBSERVED COMPONENT MODELS

Unobserved Component Model (UCM) is a structural time series model. Like other structural time series, UCM also helps us to break the response series into four components namely trend, seasonal, cyclical and regression components that can be observed from the predictor series (Harvey, 1989). The benefits of UCM are manifold. The UCM model helps to decompose the observed time series data into unobserved stochastic processes with component specific error terms (Koopman and Ooms, 2004). The error terms provide a better knowledge of the stochastic nature of the observed series and the changes in the components (Koopman and Ooms, 2004). The second advantage of the UCM is that it uses Kalman filter (1960) to generate optimal point-and interval forecasts. Thirdly and most importantly the Kalman filter algorithm expresses the observation weights of the forecasting functions as a function of previous observations (Koopman and Ooms, 2004). This is of particular interest as this helps to bring knowledge about the load from the previous hour. It is true that the unobserved state variables estimated using Kalman Filter (1960) does not consider the prior information [Vitek, 2005]. However, the framework of UCM provides prior information related to the values of unobserved components estimators. The UCM is also capable of dealing with non-Gaussian observations and nonlinear data sets (Harvey, 1989). Another advantage of UCM is that it can be applied by including some or all of the components or even adding new variables.

A general model for UCM is given by

$$y_t = \mu_t + \gamma_t + \psi_t + r_t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{m} \beta_j x_{tj} + \varepsilon \tag{4}$$

$$\varepsilon_t \sim N(0, \sigma_\varepsilon^2), \tag{5}$$

where,

y_t = Response series

μ_t = Trend component

γ_t = Seasonal component

ψ_t = Cyclical component

r_t = Seasonal component

$\sum_{i=1}^{p} \phi_i y_{t-i}$ = Regression component showing the lag values of the response variable

$\sum_{j=1}^{m} \beta_j x_{tj}$ = Regression component with predictor variables

ε = Error component or irregular component; Independent, identically distributed with mean 0 and variance σ_t^2.

In the following sections, each of the components is discussed briefly.

6.1.1. Trend Component. The trend component shows the natural trend that exists in the observed data in the absence of any disturbing factors. Published literature show that there are two ways to model a stochastic trend component—random walk model and locally linear time trend model (Harvey, 1989; Harvey 2006). The random walk model gives a trend that is approximately constant over the span of the observed series without any drift (Harvey, 1989; Harvey 2006). The random walk model of the trend component is given by:

$$\mu_t = \mu_{t-1} + \eta_t \tag{5}$$

$$\eta_t \sim i.i.d.\,\mathrm{N}(0, \sigma_\eta^2). \tag{6}$$

The second methodology, as the name speaks, is locally linear and has a slope and level. The slope introduces stochastic nature in the model. The model is given by:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t \tag{7}$$

$$\beta_t = \beta_{t-1} + \xi_t \tag{8}$$

$$\eta_t \sim i.i.d.\,\mathrm{N}(0, \sigma_\eta^2) \tag{9}$$

$$\xi_t \sim i.i.d.\,\mathrm{N}(0, \sigma_\xi^2), \tag{10}$$

where

β = Stochastic Slope

ε_t = Irregular disturbances

ξ_t = Slope disturbances

η_t = Level distubances.

In the above models the irregular, level and slope disturbances are mutually independent. It is interesting to note that if level and slope disturbances are zero, then the trend becomes deterministic. If the slope disturbance is zero then the locally lineal model turns into random walk model described earlier.

6.1.2. Cyclical Component. The general representation of the cyclical component ψ_t is by the following recursive formula

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho \begin{bmatrix} Cos\lambda & Sin\lambda \\ -Sin\lambda & Cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} v_t \\ v_t^* \end{bmatrix}, \tag{11}$$

where,

ψ = Cycle component

ρ = Damping factor and $0 \le \rho \le 1$

λ = Frequency of the cycle component

v_t and v_t^* = Mutually independent Gaussian noise component
with mean 0 and variance σ_v.

The cycle component ψ_t is modeled as a periodic function. The cycle period is given by $2\pi / \lambda$ where λ is the frequency of the cycle and range of the frequency is [$0<\lambda<\pi$]. For the frequency $0 < \lambda < \pi$, the range of cyclical component demonstrate a peak that is centered around λ. The peak becomes sharper as the damping factor reaches closer to one (Harvey, 1989). The amplitude of the cycle is $(\alpha^2 + \beta^2)^{1/2}$ with a phase angle $\tan^{-1}(\beta / \alpha)$. While the period is fixed, the amplitude is time varying. The α and β are initially set as:

$$\psi_{t=0}^2 + \psi_{t=0}^{*2} = \alpha^2 + \beta^2. \tag{12}$$

The stationarity properties of the random sequence ψ_t depend on the damping factor ρ_1. If $0 < \rho_1 < 1$, ψ_t becomes stationary with mean zero and variance $\frac{\sigma_v^2}{\rho_1^2}$.

If $\rho_1 = 1$, ψ_t is non-stationary.

The UCM is flexible enough to incorporate several cycles. So, if there exists two cycles such as daily and weakly cycle then, those two can be introduced in the same model. The two cycles will have the same formulation except for the fact that they will have differing frequencies, λ_1 and λ_1, as shown below.

$$\begin{bmatrix} \psi_{1t} \\ \psi^*_{1t} \end{bmatrix} = \rho_1 \begin{bmatrix} Cos\lambda_1 & Sin\lambda_1 \\ -Sin\lambda_1 & Cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{1t-1} \\ \psi^*_{1t-1} \end{bmatrix} + \begin{bmatrix} v_{1t} \\ v^*_{1t} \end{bmatrix} \tag{13}$$

$$\begin{bmatrix} \psi_{2t} \\ \psi^*_{2t} \end{bmatrix} = \rho_2 \begin{bmatrix} Cos\lambda_2 & Sin\lambda_2 \\ -Sin\lambda_2 & Cos\lambda_2 \end{bmatrix} \begin{bmatrix} \psi_{2t-1} \\ \psi^*_{2t-1} \end{bmatrix} + \begin{bmatrix} v_{2t} \\ v^*_{2t} \end{bmatrix}. \tag{14}$$

The subscript 1 represent the daily cycle and the subscript 2 represent the weakly cycle. Rest of the notation remains same. The actual model for y_t would have two different cyclical components-ψ_{1t} and ψ_{2t} instead of only one component, ψ_t.

6.1.3. Seasonal Component. Time series data such as electricity load or demand data, or sales often observes a seasonal pattern, which arises from regular changes in seasons or other periodic events that occur over the span of of year.. The seasonal effect can be modeled in different ways. One of the ways to model the seasonal component is using dummy variables (Harvey, 2006) and is given by—

$$\sum_{i=0}^{s-1} \gamma_{t-i} = w_t, \tag{14}$$

$$w_t \sim \text{i.i.d. } N(0,\sigma_w^2). \tag{15}$$

In the above model for the seasonal component, γ_t is modeled as a stochastic periodic pattern. The period is denoted by the integers. For example, if the period of a monthly dataset with a seasonal component is 12, and *t* denotes December of a given year, then the variables γ_{t-11}, $\gamma_{t-10}, \ldots, \gamma_t$ denote seasonal components for January, February, etc. up to December.

6.1.4. Autoregressive Component. Generally, an autoregressive (AR) model can explain many data sets. However, the AR models alone can do a poor job when the data contains seasonal or cyclical effects. This is because the seasonal variation may be slow and this may require the simple AR model to use long seasonal lags. Nevertheless, combination of an autoregression component with other stochastic seasonal components may produce a very powerful explanatory model (Harvey and Scott, 1994). The autoregressive model of order one is given by:

$$r_t = \rho r_{t-1} + \nu_t \tag{16}$$

$$\nu_t \sim i.i.d.\ N(0, \sigma_\nu^2) \tag{17}$$

$$0 \leq \rho < 1. \tag{18}$$

6.1.5. Regression Components. The regression components $\sum_{i=1}^{p} \phi_i y_{t-i}$ and $\sum_{j=1}^{m} \beta_j x_{tj}$, give the UCM the flexibility to add other explanatory variables, lags or any kind of transformations that may be applied.

6.2. THE GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTICITY (GARCH) MODEL

While the simple AR model accounts for the autocorrelation present in the dataset, the generalized autoregressive conditional heteroscedasticity or GARCH model is employed to model the heteroscedasticity present in the series (Bollerslev, 1986). The challenge in modeling electricity price, which shows high volatility, is that the error variance, conditional on the past values, is not constant. Regression models, even those with an autoregressive error, assume a constant volatility in the residuals which does not make such a model suitable for electricity price data. GARCH based models method that can handle such heteroscedasticity. The GARCH (p,q) based regression model which includes *an* m^{th} order autoregressive error term is given in the equations (19)-(23).

The following GARCH based model is termed as AR(m)-GARCH(p,q) model.

$$y_t = x_t^{'}\beta + \nu_t \tag{19}$$

$$\nu_t = \varepsilon_t - \varphi_1 \nu_{t-1} - \ldots - \varphi_m \nu_{t-m} \tag{20}$$

$$\varepsilon_t = \sqrt{h_t} e_t \tag{21}$$

$$e_t \sim N(0,1) \tag{22}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j}. \tag{23}$$

If p and q are 1, then the error process is GARCH (1, 1) and the above equation becomes:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1}. \tag{24}$$

The quantity $\sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2$ is called the ARCH(q) component and $\sum_{j=1}^{p} \gamma_j h_{t-j}$ is called the GARCH(p) component. The ARCH (q) component indicates a short memory process whereas GARCH component represents the long term memory process of the model. With ARCH component, the model considers only the last q squared residuals in calculating time varying variance in the residuals. The ARCH components help to capture the short term volatility. The GARCH component captures all the previous squared residuals or errors terms up to time t to estimate the time varying variance for time t.

7. BUILDING SIMULATION MODELS

Figure 7.1 summarizes different important variables discussed in chapters 3, 4 and 5. The figure describes how DAD, RTL, DAP and RTP are influenced by different variables and how they interact between themselves.

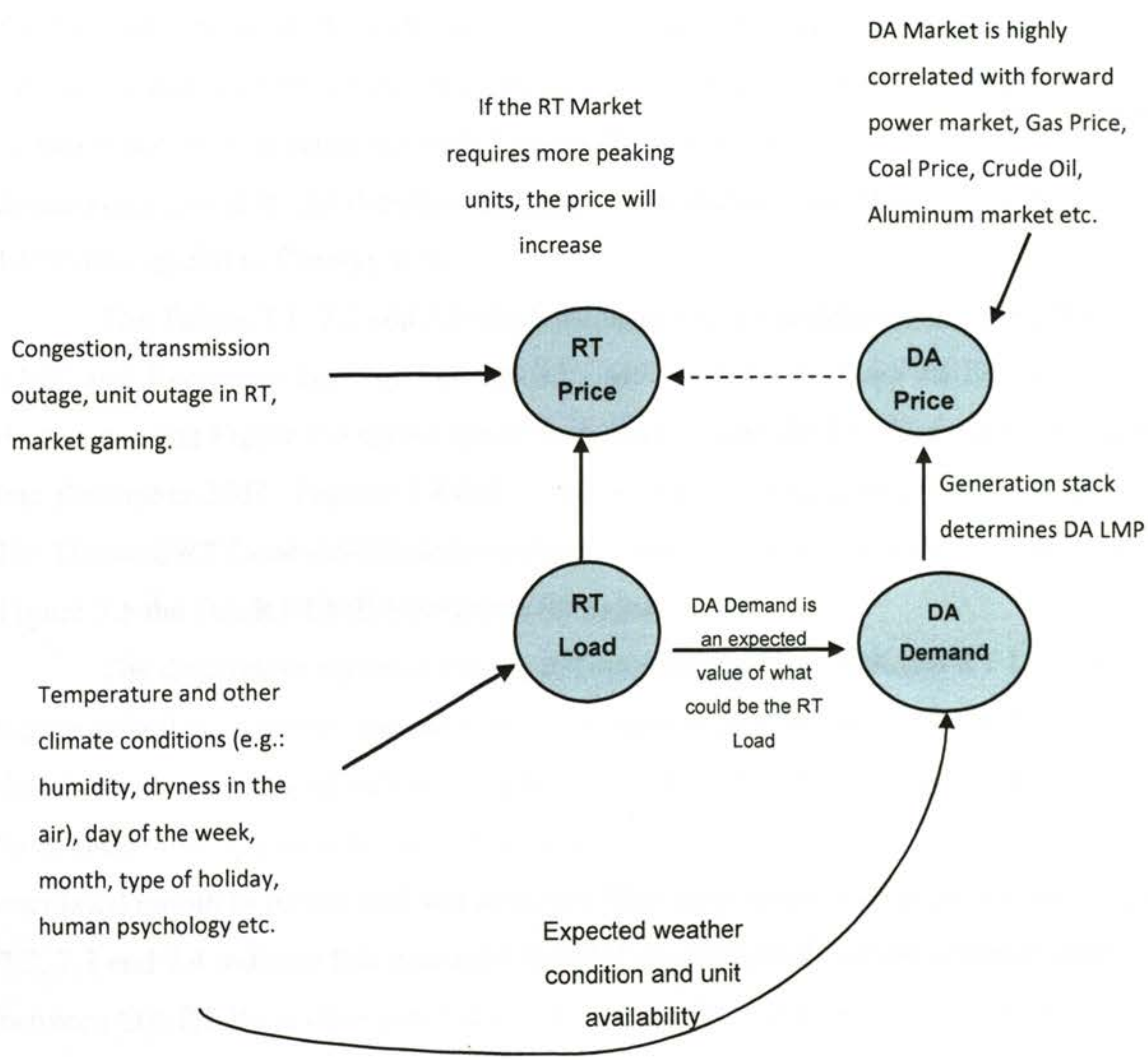

Figure 7.1. Factors Influencing the DA/RT Market

In the proposed simulation model in this dissertation, interactions among DAD, RTL, DAP and RTP (as shown in Figure 7.1) are considered. Nevertheless, relationship between power price and other commodity (such as gas or oil) prices is not addressed. This dissertation uses publicly available data from MISO webpage[9].

7.1. PRELIMINARY DATA ANALYSIS AND MODEL BUILDING

This dissertation seeks to understand the dynamic relationship between the price and load better. This requires test the relationship between DA and RT price convergence or divergence and the change in DA demand and RT Load. The divergence is defined as the difference between RT LMP and DA LMP. Also, the relationship between cleared virtual volume and DA/RT prices is checked to investigate if there exists any convergence or divergence in DA/RT prices due to the cleared virtual volume. This dissertation considers the demand, load and virtual trading data related to MISO and the LMP data related to Cinergy hub.

The Tables 7.1, 7.2 and 7.3 show the descriptive statistics for the DA LMP, RT LMP, and divergence between DA and RT LMP. Figure 7.2 shows the DA/RT price divergence and Figure 7.3 shows the RTL deviation from the DAD between June 2006 and December 2007. Figures 7.4 and 7.5 show DA/RT Price divergence as compared to DA Demand/RT Load deviation percentage. Figure 7.4 represents data for 2007 and Figure 7.5 the DA/RT LMP divergence for January 2007.

The descriptive statistics clearly indicates that both the DA and RT LMP have higher volatility, kurtosis, and skewness. The distribution has relatively fat tails and the data is positively skewed indicating spikes in the RT LMP. The data confirms that there have been more spikes in the RT LMP compared to the DA LMP. The divergence oscillated month to month and was different from peak hours and off peak hours. Figures 7.2, 7.3 and 7.4 indicate that a straight forward general trend can not be established between DA/RT Price divergence and DA Demand/RT Load deviation. Although in some hours or months, higher RT Load resulted in higher price divergence, it can not be generalized for sure that higher demand always causes higher DA price.

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[9] MISO website: http://www.midwestiso.org/

Table 7.1. Descriptive Statistics of Peak Hour Cinergy Hub Price

Peak Hours Price at Cinergy hub (June 2006 - December 2006)					
DA LMP	***Stat***	***RT LMP***	***Stat***	***RT-DA LMP***	***Stat***
Mean	53.02	Mean	49.66	Mean	3.36
Median	47.34	Median	40.92	Median	4.33
Standard Deviation	23.64	Standard Deviation	30.38	Standard Deviation	22.99
Sample Variance	558.75	Sample Variance	922.99	Sample Variance	528.65
Kurtosis	4.12	Kurtosis	23.23	Kurtosis	19.79
Skewness	1.57	Skewness	3.28	Skewness	1.93
Range	180.80	Range	458.95	Range	423.69
Minimum	18.67	Minimum	-2.64	Minimum	-316.46
Maximum	199.47	Maximum	456.31	Maximum	107.23

Table 7.2. Descriptive Statistics of Peak Hour Cinergy Hub Price

Peak Hours Price at Cinergy hub (January 2007 - December 2007)					
DA LMP	***Stat***	***RT LMP***	***Stat***	***RT-DA LMP***	***Stat***
Mean	61.50	Mean	60.94	Mean	0.56
Median	58.85	Median	54.15	Median	3.64
Standard Deviation	22.93	Standard Deviation	35.81	Standard Deviation	29.87
Sample Variance	525.67	Sample Variance	1282.12	Sample Variance	892.18
Kurtosis	1.03	Kurtosis	43.60	Kurtosis	64.29
Skewness	0.78	Skewness	3.53	Skewness	3.87
Range	171.93	Range	775.59	Range	768.69
Minimum	18.30	Minimum	-6.04	Minimum	-654.55
Maximum	190.23	Maximum	769.55	Maximum	114.14

Table 7.3. Descriptive Statistics of Off Peak Cinergy Hub Price

Off Peak Cinergy Hub Price (Jun 2006-Dec 2007)					
DA LMP	***Statistics***	***RT LMP***	***Statistics***	***RT-DA Price***	***Statistics***
Mean	31.82	Mean	31.33	Mean	(0.49)
Median	25.37	Median	23.75	Median	(1.15)
Mode	25.00	Mode	19.56	Mode	(2.55)
Standard Deviation	16.97	Standard Deviation	21.51	Standard Deviation	15.49
Sample Variance	287.93	Sample Variance	462.66	Sample Variance	239.99
Kurtosis	4.66	Kurtosis	13.01	Kurtosis	19.06
Skewness	2.00	Skewness	2.87	Skewness	2.31
Range	125.00	Range	311.53	Range	272.02
Minimum	8.00	Minimum	(55.44)	Minimum	(81.82)
Maximum	133.00	Maximum	256.09	Maximum	190.20

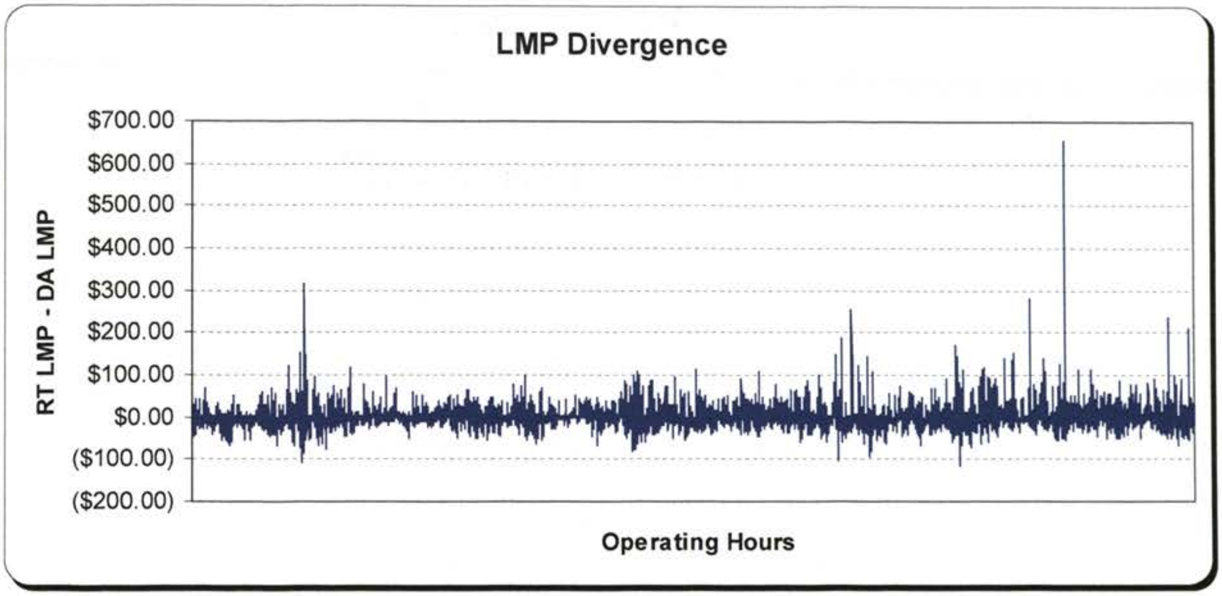

Figure 7.2. LMP Divergence between DA and RT Market

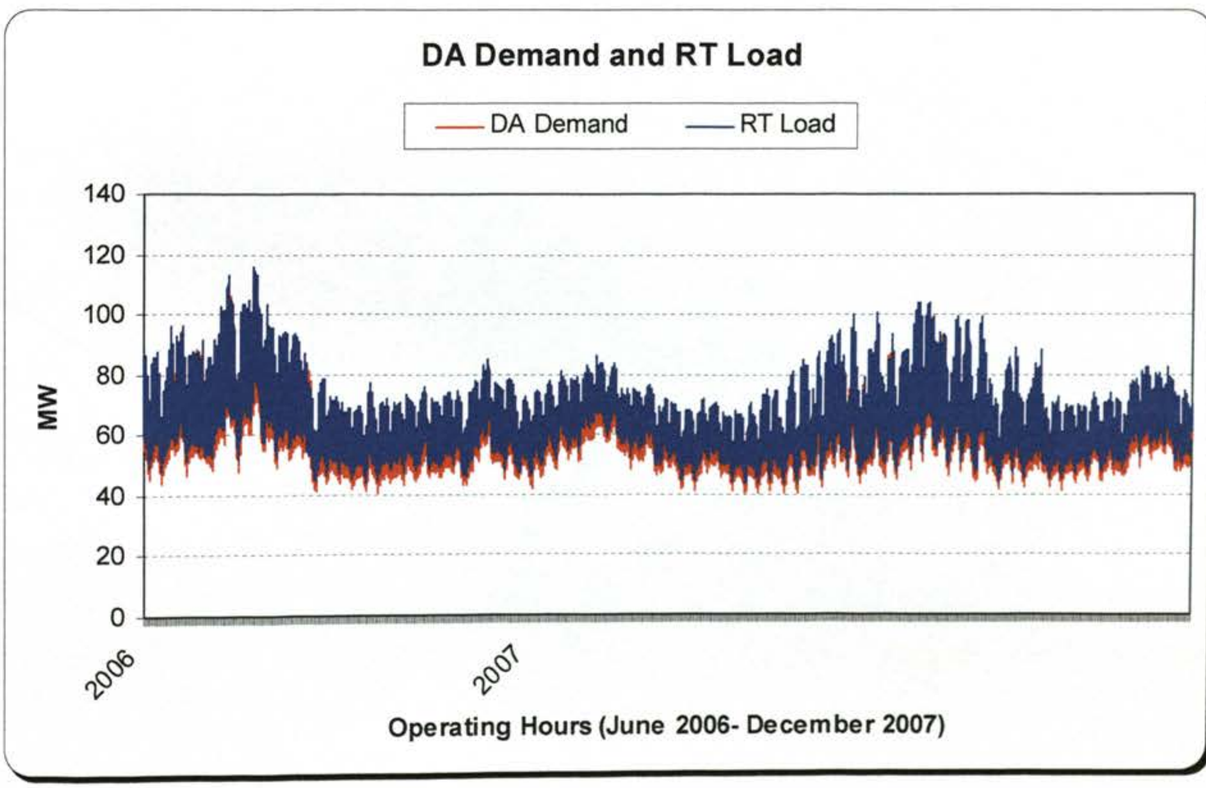

Figure 7.3. DA Demand and RT Load

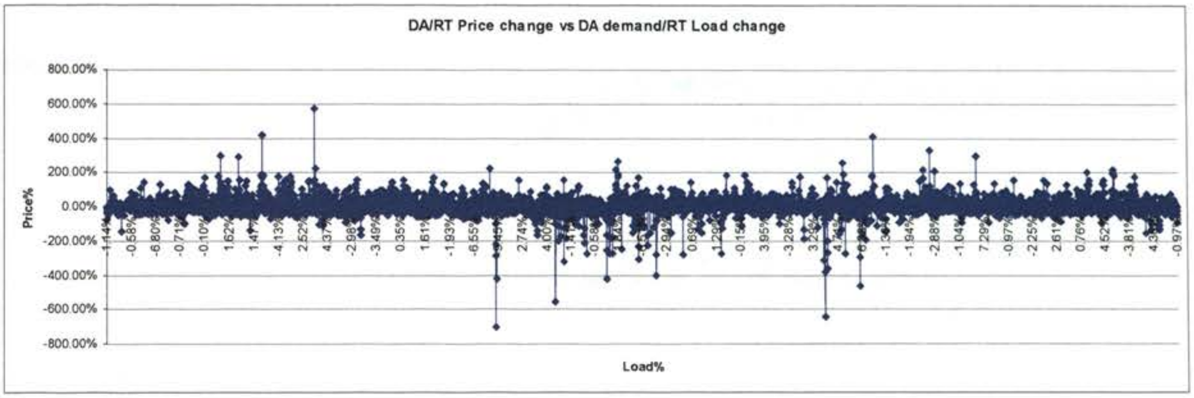

Figure 7.4. DA/RT Price Divergence vs. DA Demand/RT Load Change

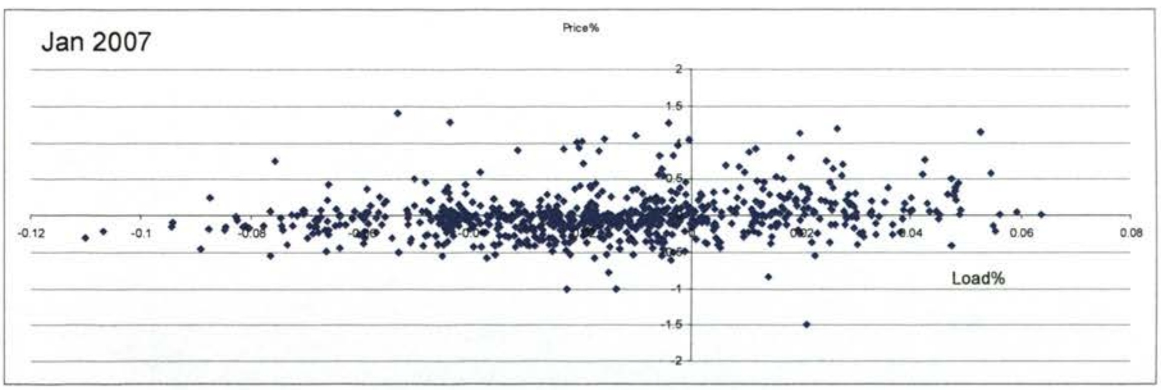

Figure 7.5. DA/RT Price Divergence vs. DA Demand/RT Load Change

The amount of cleared virtual bids and offers are also considered to investigate if the price divergence is caused by the amount of cleared virtual bids and offers. Figure 7.6 shows the cleared virtual bids, offers and deviation between them for each operating hour during June 2006-December 2007. Figure 7.7 shows the relationship between the price divergence and the virtual bids and offer divergence. Once again, a general trend cannot be established that would indicate that the price divergence between DA and RT is due to the divergence in the cleared virtual bids and offers. The hypothesis to test the correlation between the difference of virtual bids and offers cleared and price divergence failed at 95% confidence interval.

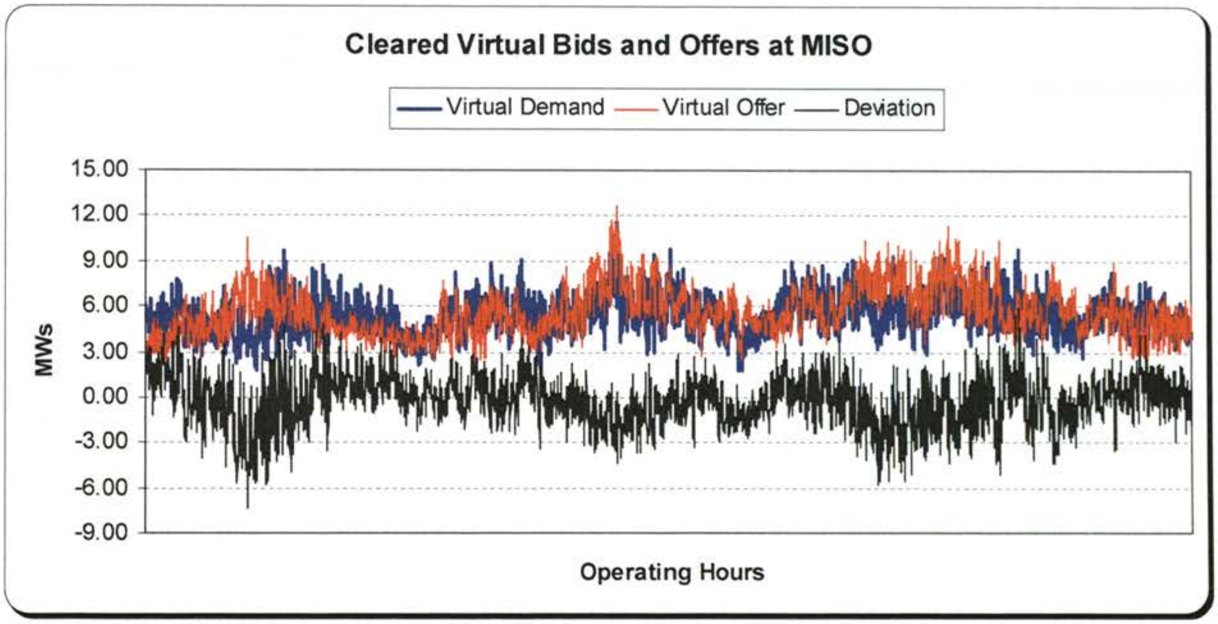

Figure 7.6. Virtual Bids, Offers and Deviation

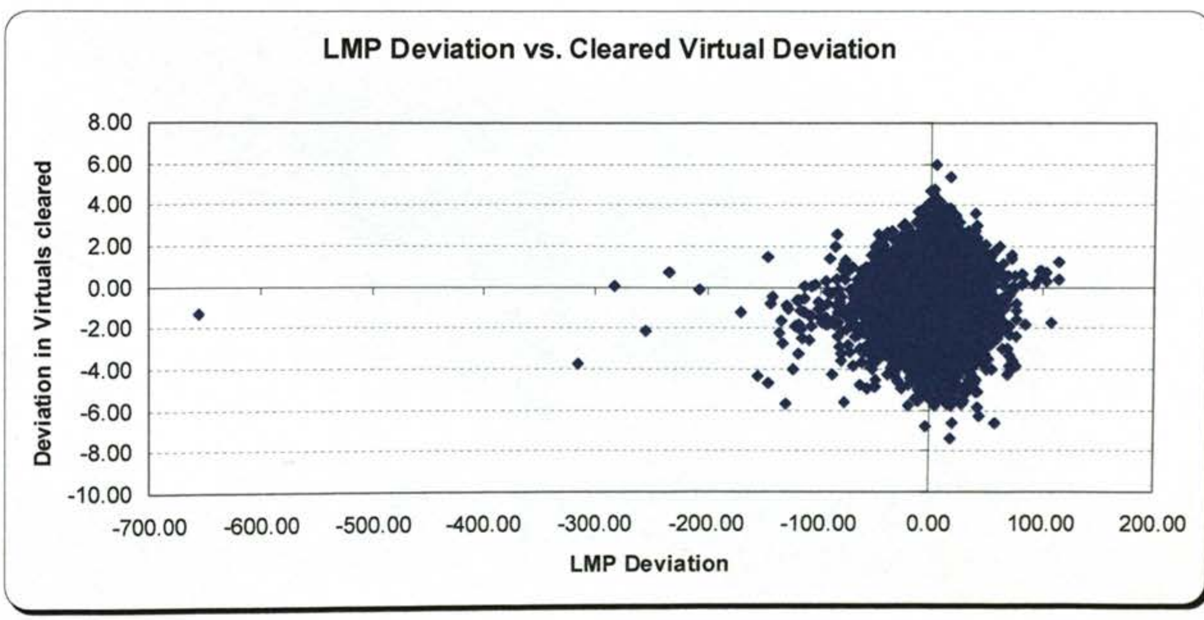

Figure 7.7. LMP Deviation vs. Virtual Deviation

Spectral analysis of the Cinergy hub data set (for the period June 1, 2006 to December 31, 2007) was conducted to examine the cyclical and seasonal behavior of the price and load. The following section shows the results of the spectral analysis of the Cinergy hub data set. The spectral analysis identified that there is a daily, weekly and yearly cycle in the DA and RT demand, load and price. The analysis also identified a potential 83 day (approximate) cycle in the price data set. The daily, weekly and yearly cycles can be justified from the fundamental understanding of how electricity market works. During the weekdays the consumption of the electricity increases as there are more industrial consumers (such as office building etc.). The yearly cycle explains the seasonal component of the data. The 83 day cycle cannot be justified as more data is required to check if this cycle actually reoccurs every year or not.

As it has been mentioned in the literature, weather component is the most crucial piece in the load model. In modeling the load pattern across the footprint of MISO or any other ISO or region, one needs to take care of the weather information from all the stations in that footprint. Because of unavailability of such a database, this dissertation considers seven large cities, namely Chicago, Indianapolis, Detroit, Minneapolis, St Louis, Cincinnati and Milwaukee for weather related information. These cities are located across MISO footprint and would help us explain average weather affect on the MISO load, demand and price. Figure 7.8 shows the cities across MISO footprints which have been considered in our model. Figure 7.9 shows the daily minimum humidity data from the seven cities are shown in Figure 7.8. Appendix A shows rest of the weather data.

Tests were conducted for autoregression in the lagged terms and for any cycle present in the DA Demand, RT Load and the price data. The hypothesis test was conducted under UCM set up and the daily and yearly cycles and autocorrelation terms become significant. However, it was not possible to get a complete understanding of how the load or price varied just by setting these components alone. The UCM took longer time to converge with yearly cycle component. Although from this test the yearly cycle appears to be significant, it was not convincing to include the yearly cycle component in the final model because of lack of enough data to test. Table 7.4 shows these hypothesis results for DA Demand and Table 7.5 shows the hypothesis results for RT Load.

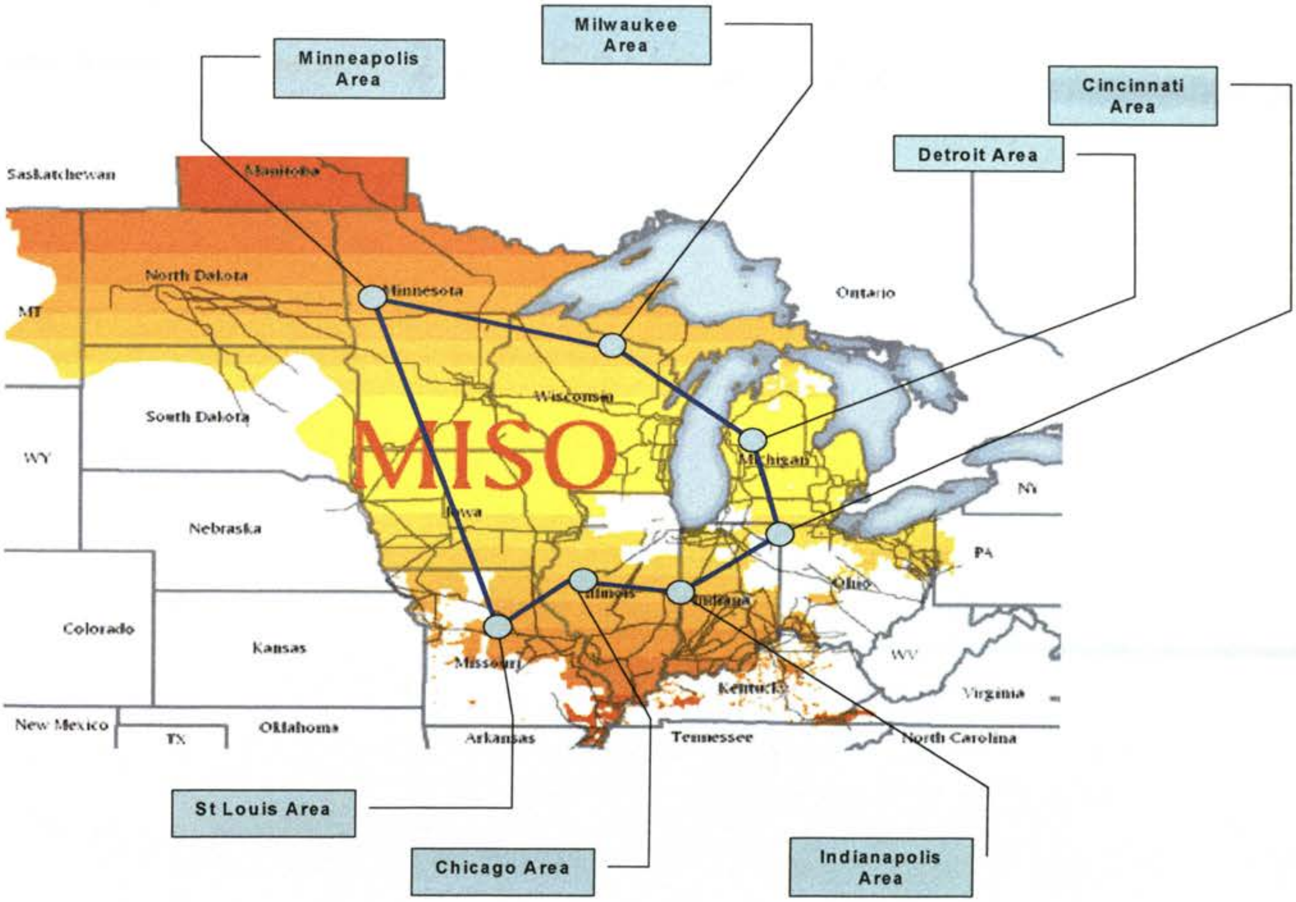

Figure 7.8. Prominent Cities across MISO Footprint

Weather factors which influence the electricity market are namely temperature, humidity, wind speed, cloud cover, dew point, precipitation, rain, thunderstorms, and snow. However, because of data limitation, this dissertation considers daily maximum, minimum and average of the temperature, humidity, wind speed, cloud cover, and dew point only.

Principal Component Analysis (PCA) was used to summarize weather variations across the aforementioned seven cities across MISO footprint. PCA is a strong tool that exploits the covariance structure among the variables to produce linear combination of the variables (called Principal Components) that explains the variation in the data. If there is strong correlation among variables, then a few Principal Components can explain most of the variation. Thus PCA is helpful in dimension reduction. With PCA, one can explain a certain p variables ($p>1$) and information provided by these p variables by using k components ($p>k>0$).

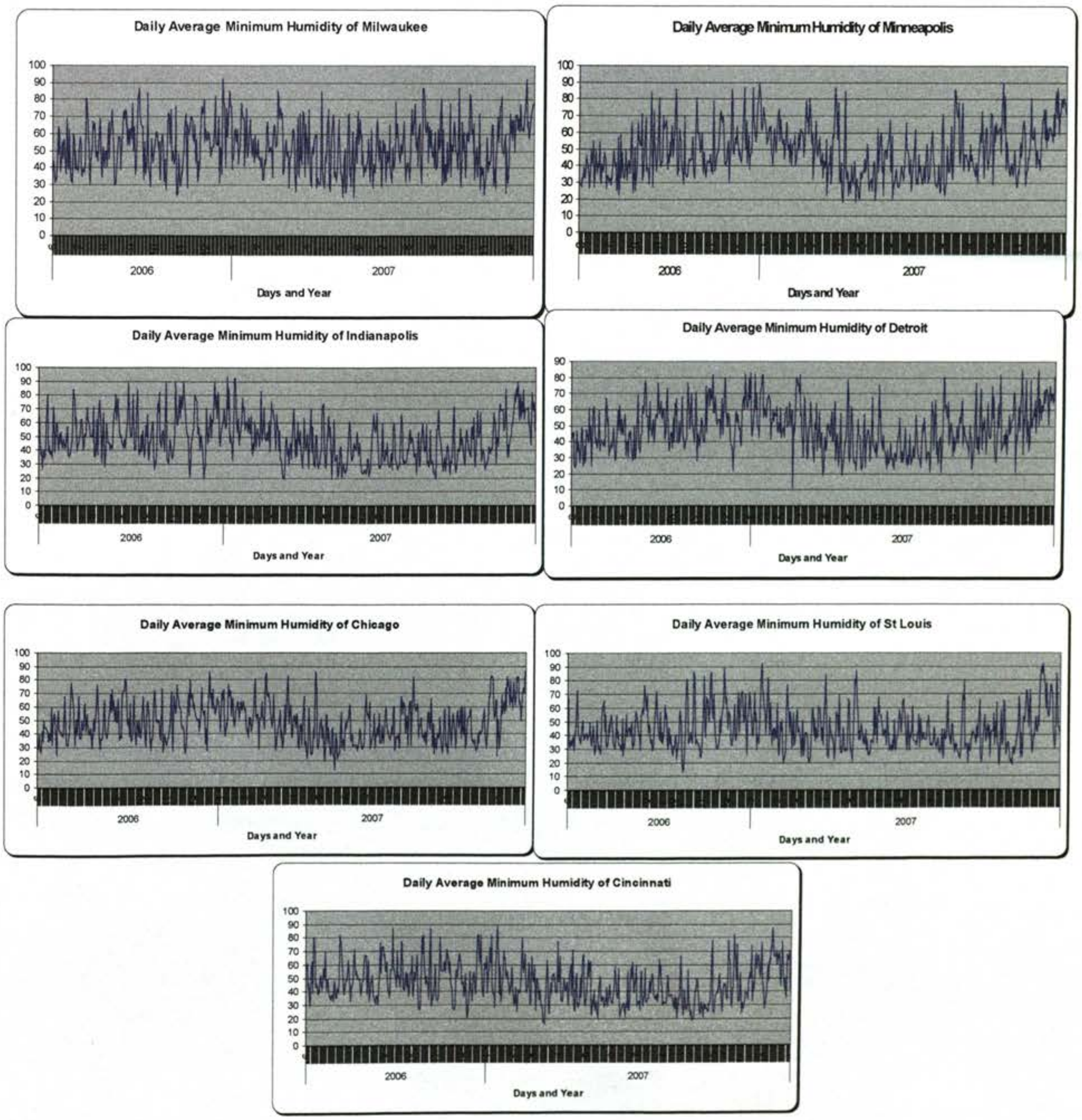

Figure 7.9. Daily Minimum Humidity Data Observed in Seven Cities across MISO

Table 7.4. Test for Cycle Components and Autoregression in DA Demand

Component	Parameter	Estimate	Approx Std Error	t Value	Approx Pr > |t|
Error component	Error Variance	1.4556E-10	1.66748E-7	0.00	<.0001
Autoregression component	Damping Factor	0.98570	11.50865	0.09	<.0001
Autoregression component	Error Variance	8.89239E-9	0.00001904	0.00	<.0001
Yearly cycle component ψ_{2t}	Damping Factor	0.99994	2.34481E-6	426447	<.0001
Yearly cycle component ψ_{2t}	Error Variance	0.42151	.	.	.
Daily cycle component ψ_{1t}	Damping Factor	0.98928	0.0008856	1117.03	<.0001
Daily cycle component ψ_{1t}	Error Variance	1.34971	0.11025	12.24	<.0001

This research considered both simple average temperature of the seven cities considered and the PCs of Heating degree days (HDD) and cooling degree days (CDD) as explanatory variables. However, the PCs of HDD and CDD are found to be better explanatory variable for load and price models than the simple average. The PCA indicates that the first principal component describes almost 90% of the variations in HDD and CDD across these seven cities representing MISO footprint. The second principal component for both HDD and CDD did not only appear to be insignificant at the 0.05 significance level, but also could not improve the R-Square or Adjusted R-Square or AIC value. The square of the temperature, HDD and CDD and PC of these three variables have also been tried as explanatory variables. The square terms appeared to be statistically insignificant. The PCs for both HDD and CDD are shown in Appendix B along with PCs of other weather variables.

Table 7.5. Test for Cycle Components and Autoregression in RT Load

Component	Parameter	Estimate	Approx Std Error	t Value	Approx Pr > |t|
Error component	Error Variance	4.58907E-10	3.64489E-7	0.00	<.0001
Autoregressive	Damping Factor	0.99057	4.29794	0.23	<.0001
Autoregressive	Error Variance	5.177117E-8	0.00005820	0.00	<.0001
Yearly cycle component ψ_{2t}	Damping Factor	0.99992	3.1631E-6	316121	<.0001
Yearly cycle component ψ_{2t}	Error Variance	0.52799	0.0051966	101.60	<.0001
Daily cycle component ψ_{1t}	Damping Factor	0.98482	0.0010593	929.69	<.0001
Daily cycle component ψ_{1t}	Error Variance	1.86381	0.12824	14.53	<.0001
Temperature	Coefficient	0.03972	0.01492	2.66	0.0077

Next other climate variables such as cloud cover, dew point (maximum, minimum and mean dew point measure of the day), wind speed (maximum, minimum and average wind speed measure of the day), humidity (maximum, minimum and average humidity of the day) and precipitation (maximum, minimum and average precipitation of the day) during the time period Jun 1, 2006-Dec 31, 2006 are considered as explanatory variables. Principal component analysis was applied on these variables for dimension reduction purpose. Appendix B shows the PCA results for these variables. The principal components that explain at least 90% of the variability in the data set are used to build the proposed simulation models. However, not all the PCs are statistically significant. There may be several reasons why these PCs are statistically insignificant for the propose simulation model, including the facts that they represent only a few cities in the MISO foot print or these variables do not represent the hourly variation. The weather data represent daily average or maximum or minimum. Electricity load or demand change quickly during certain hours depending on the weather. For an example, during summer, it may be very hot a morning which will increase the load; however, if there is a thunderstorm in the afternoon, the load may decrease during the thunderstorm periods and the hours following the thunderstorm. Load may go back to the original level the very next day. Similarly, if there is congestion or unit or transmission line outage during some particular hours, there may be a sudden price spike. However, these variations across hours would not be captured by daily average or maximum or minimum weather variables. Certain PCs are also rejected if including lesser number of variables did not reduce the adjusted R-square value or increase the AIC value significantly. This helps to make the model parsimonious and reduce prediction error. It also helps to minimize simulation time.

The following equations (equations #25-35) show the first principal components for different weather variables used in this analysis. Please refer to the Appendix B for details on the Eigen vectors that constitute all the principal components. In the following equations, PC1 stands for the Principal Component 1. The weather variable is indicated next to "PC1". In the right hand side of the equations, the city names are shown. The city name indicates for the weather variable for that city.

Let us assume,

$PC1\_Cloud\_Cover$ = First Principal Component for Cloud Cover

$PC1\_\Pr ecipitation$ = First Principal Component for Precipitation

$PC1\_Mean\_Wind\_Speed$ = First Principal Component for Mean Wind Speed

$PC1\_Max\_Wind\_Speed$ = First Principal Component for Maximum Wind Speed

$PC1\_Mean\_Humidity$ = First Principal Component for Mean Humidity

$PC1\_Max\_Humidity$ = First Principal Component for Maximum Humidity

$PC1\_Min\_Humidity$ = First Principal Component for Minimum Humidity

$PC1\_Mean\_DewPo\text{int}$ = First Principal Component for Dew Point

$PC1\_Temp\_CDD$ = First Principal Component for Cooling Degree Days

$C1\_Temp\_HDD$ = First Principal Component for Heating Degree Days

Then,

$$\begin{aligned} PC1\_Cloud\_Cover = 0.2336 * Minneapolis &+ 0.4176 * Milwaukee + \\ &+ 0.4493 * Indianapolis + 0.3644 * Detroit + \\ &+ 0.4496 * Chicago + 0.3339 * StLouis + \\ &+ 0.3500 * Cincinnati, \end{aligned} \tag{25}$$

$$\begin{aligned} PC1\_\Pr ecipitation = 0.2716 * Minneapolis &+ 0.3333 * Milwaukee + \\ &+ 0.5050 * Indianapolis + 0.4394 * Detroit + \\ &+ 0.3748 * Chicago + 0.3628 * StLouis + \\ &+ 0.4096 * Cincinnati, \end{aligned} \tag{26}$$

$$\begin{aligned} PC1\_Mean\_Wind\_Speed = 0.2599 * Minneapolis &+ 0.3963 * Milwaukee \\ &+ 0.4546 * Indianapolis + 0.3662 * Detroit + \\ &+ 0.4284 * Chicago + 0.3842 * StLouis \\ &+ 0.3213 * Cincinnati, \end{aligned} \tag{27}$$

$$\begin{aligned} PC1\_Max\_Wind\_Speed = 0.1945 * Minneapolis &+ 0.3927 * Milwaukee + \\ &+ 0.4405 * Indianapolis + 0.3950 * Detroit + \\ &+ 0.4258 * Chicago + 0.3517 * StLouis + \\ &+ 0.3912 * Cincinnati, \end{aligned} \tag{28}$$

$$\begin{aligned} PC1\_Mean\_Humidity = 0.2719 * Minneapolis &+ 0.3873 * Milwaukee + \\ &+ 0.4240 * Indianapolis + 0.3889 * Detroit + \\ &+ 0.4411 * Chicago + 0.3524 * StLouis + \\ &+ 0.3549 * Cincinnati, \end{aligned} \tag{29}$$

$$\begin{aligned}PC1\_Max\_Humidity = 0.2496*Minneapolis &+ 0.4308*Milwaukee + \\ &+ 0.4093*Indianapolis + 0.3856*Detroit + \\ &+ 0.4666*Chicago + 0.3752*StLouis + \\ &+ 0.2814*Cincinnati,\end{aligned} \tag{30}$$

$$\begin{aligned}PC1\_Min\_Humidity = 0.26353*Minneapolis &+ 0.3711*Milwaukee + \\ &+ 0.4282*Indianapolis + 0.3920*Detroit + \\ &+ 0.4305*Chicago + 0.3509*StLouis \\ &+ 0.3836*Cincinnati,\end{aligned} \tag{31}$$

$$\begin{aligned}PC1\_Mean\_DewPo\text{int} = 0.3644*Minneapolis &+ 0.3828*Milwaukee + \\ &+ 0.3815*Indianapolis + 0.3762*Detroit + \\ &+ 0.3815*Chicago + 0.3771*StLouis + \\ &+ 0.3780*Cincinnati,\end{aligned} \tag{32}$$

$$\begin{aligned}PC1\_Max\_DewPo\text{int} = 0.3613*Minneapolis &+ 0.3836*Milwaukee + \\ &+ 0.3819*Indianapolis + 0.3781*Detroit + \\ &+ 0.3858*Chicago + 0.3773*StLouis + \\ &+ 0.3769*Cincinnati,\end{aligned} \tag{33}$$

$$\begin{aligned}PC1\_Temp\_CDD = 0.3740*Minneapolis &+ 0.3800*Milwaukee + \\ &+ 0.3777*Indianapolis + 0.3817*Detroit + \\ &+ 0.3728*Chicago + 0.3795*StLouis + \\ &+ 0.3797*Cincinnati,\end{aligned} \tag{34}$$

$$\begin{aligned}PC1\_Temp\_HDD = 0.3497*Minneapolis &+ 0.3742*Milwaukee + \\ &+ 0.3883*Indianapolis + 0.3827*Detroit + \\ &+ 0.3943*Chicago + 0.3781*StLouis + \\ &+ 0.3775*Cincinnati.\end{aligned} \tag{35}$$

7.2. FITTING SIMULATION MODELS

The preliminary analysis of the load and demand data shows that the DA demand and RT load observed at the MISO follow daily cycles. The load and demand also changes based on seasonality, which gives the suspicion that there should be a seasonal variable. The UCM model used for this simulation model should help identifying such cyclical, season components by itself. However, given the nature of the data, the model takes longer time to run. In this dissertation, the UCM model is used to account only for the daily cycle component. A set of dummy variables are added to the overall model.

These dummy variables act as regressor variables. The dummy variables account for the seasonality, part of the week, and part of the day (peak and off peak). Comparison of this model with other models that did not include the dummy variables but instead included standard UCM cyclical components representing weekly and yearly (seasonal) cycles showed that the model with the dummy variables did as well as the model with UCM cyclical components, based on adjusted R^2 and AIC criteria. Thus, a simpler model was constructed using dummy variable terms.

The weekly cycle is clearly not sinusoidal. The cyclical nature arises due to weekends being different from weekdays. Thus the use of a dummy variable is more appropriate than employing a sinusoidal cyclical component.

The seasonality is defined based on the Fernandez-Morales (2003). The dummy variables representing seasonality are:

i. Summer months (July, August, and September): Dummy Variable 1 is "0" and Dummy Variable 2 is "0."

ii. Winter months (November, December, January, and February): Dummy Variable 1 is "1" and Dummy Variable 2 is "0."

iii. Shoulder months (March, April, May, June and November): Dummy Variable 1 is 0 and Dummy Variable 2 is 1.

Since people's electricity usage change depending on the day of the week and time of the day, two other dummy variables are added recognizing part of the week and period of the day. These dummy variables are:

i) Peak/Off Peak period of the day: "1" for Peak periods and "0" for off peak period

ii) Weekday/Weekend: "1" for weekday and "0" for weekend

Although the Unobserved Component Model (UCM) has four components, the final model consists of only one component other than the regressor variables and the irregular component. The UCM component represents the daily cycle. The details of the daily cycle component for DA demand are shown in Table 7.6. The trend component was rejected from the final model as the trend component is not very significant.

The general representation of the daily cycle component ψ_t is shown in equation (18) and has been modeled using a recursive algorithm. This model can be described as follows (The recursive formula shown below addresses the stochastic nature of the cycle):

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho \begin{bmatrix} Cos\lambda & Sin\lambda \\ -Sin\lambda & Cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} \nu_t \\ \nu_t^* \end{bmatrix} \tag{36}$$

where, $0 \le \rho \le 1$, and the white noise terms ν_t and ν_t^* are $IN(0, \sigma_\nu^2)$ (IN stands for Independent Normally distributed) variables.

The daily cycle component is modeled as a periodic function. The cycle period is given by $2\pi / \lambda$ where λ is the frequency of the cycle [0< λ < π]. The final model is selected based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The smaller the AIC or BIC is, the better the model is.

Table 7.6. Summary of Daily Cycles (DA Demand)

Summary of Cycles							
Name	Type	Period	Frequency	Damping Factor	Final Amplitude	Cycle Variance	Error Variance
Cycle	Stationary	24.00000	0.26180	0.96714	11.91544	76.38400	4.93748

7.2.1. DA Demand Model. Finally, the DA Demand model is expressed as a function of the following components and regressor variables.

1. Components of Unobserved Component Model (UCM)
    a. Irregular component or the disturbance component
    b. Daily cycle component
2. Regressor variables
    a. First Principal Components of HDD

b. First Principal Components of CDD

c. First, second, third and fourth Principal Components of Daily Minimum Humidity

d. First, second, third and fourth Principal Components of Daily Maximum Wind Velocity

e. First, second, third, fourth and fifth Principal Components of Daily Mean Wind Velocity

f. First, second, third, fourth and fifth Principal Components of Daily Precipitation

g. First, second, and third Principal Components of Daily cloud cover measurement

h. Dummy variables indicating

    i. Peak/Off Peak period of the day,

    ii. Weekday/Weekend and

    iii. Season (Summer/Shoulder/Winter months).

The DA Demand model has the following mathematical expression:

$$\breve{L}_t = I + \psi_t + \sum C_i R_i \tag{37}$$

where,

$\breve{L}_t$ = DA Demand

I = Irregular component

ψ_t = Daily cycle component of UCM

C_i = Coefficient of regression for ith regressor

R_i = ith Regressor.

The AIC and BIC values for the fitted DA demand model is given in Table 7.7. The Regression coefficients C_i and Damping Factor for Cyclical Component of UCM and value for the irregular component are given in Table 7.8. In this table, PC1, PC2, PC3, PC4 and PC5 represent the First, second, third, fourth and fifth Principal Components of that particular variable. Table 7.8 also shows the estimated standard error and *t* statistic values for each variable in the model. One important fact to note is that the error variance associated with the daily cycle is significantly different from zero. This indicates that the daily cycle is not deterministic.

Table 7.7. Likelihood Based Fit Statistics for DA Demand Model

Likelihood Based Fit Statistics	
Akaike Information Criterion (AIC)	63518
Bayesian Information Criterion (BIC)	63751

Table 7.8. Final Estimates of the DA Demand Model

Component	Parameter	Estimate	Approx Std Error	t Value	Approx Pr > |t|
Irregular Component	Error Variance	1.05933E-7	9.77266E-6	0.01	0.9914
Daily Cycle Component	Damping Factor	0.96714	0.0015758	613.76	<.0001
Daily Cycle Component	Error Variance	4.93748	0.23354	21.14	<.0001
Dummy Variable: Peak/Off Peak	Coefficient	3.24391	0.08816	36.80	<.0001
Dummy Variable: Weekday/Weekend	Coefficient	4.75425	0.14065	33.80	<.0001
PC1 for HDD	Coefficient	0.27157	0.01279	21.24	<.0001

Table 7.8 (Continued). Final Estimates of the DA Demand Model

Component	Parameter	Estimate	Approx Std Error	t Value	Approx Pr > |t|
PC1 for HDD for Next day	Coefficient	0.34917	0.01210	28.86	<.0001
PC1 for CDD	Coefficient	0.09662	0.0030168	32.03	<.0001
Dummy Variable: Season 1	Coefficient	3.87488	0.21192	18.28	<.0001
Dummy Variable: Season 2	Coefficient	-3.26998	0.25655	-12.75	<.0001
PC1 for Min Humidity	Coefficient	0.23298	0.0028184	82.66	<.0001
PC2 for Min Humidity	Coefficient	0.04899	0.0052713	9.29	<.0001
PC3 for Min Humidity	Coefficient	0.07210	0.0057839	12.47	<.0001
PC4 for Min Humidity	Coefficient	0.02834	0.0068785	4.12	<.0001
PC1 for Max Wind Speed	Coefficient	0.63719	0.01068	59.65	<.0001
PC2 for Max Wind Speed	Coefficient	0.27705	0.01485	18.66	<.0001
PC3 for Max Wind Speed	Coefficient	-0.08672	0.01469	-5.90	<.0001
PC4 for Max Wind Speed	Coefficient	0.09610	0.01678	5.73	<.0001
PC1 for Mean Wind Speed	Coefficient	-0.37646	0.01846	-20.40	<.0001
PC2 for Mean Wind Speed	Coefficient	-0.18672	0.02024	-9.23	<.0001
PC3 for Mean Wind Speed	Coefficient	0.21156	0.02218	9.54	<.0001
PC4 for Mean Wind Speed	Coefficient	-0.18099	0.02170	-8.34	<.0001
PC5 for Mean Wind Speed	Coefficient	0.19371	0.02527	7.67	<.0001
PC1 for Precipitation	Coefficient	-6.77317	0.18352	-36.91	<.0001
PC2 for Precipitation	Coefficient	-2.11522	0.23422	-9.03	<.0001
PC3 for Precipitation	Coefficient	-2.44678	0.28437	-8.60	<.0001
PC4 for Precipitation	Coefficient	2.33523	0.27100	8.62	<.0001
PC5 for Precipitation	Coefficient	-1.71043	0.30530	-5.60	<.0001
PC1 for Cloud Cover	Coefficient	-0.27438	0.01903	-14.42	<.0001

Table 7.8 (Continued). Final Estimates of the DA Demand Model

Component	Parameter	Estimate	Approx Std Error	t Value	Approx Pr > |t|
PC2 for Cloud Cover	Coefficient	-0.43525	0.02566	-16.96	<.0001
PC3 for Cloud Cover	Coefficient	-0.21062	0.02619	-8.04	<.0001

The model's fit is described by the Mean Absolute Percentage Error (MAPE), R-Square and Adjusted R-Square. Generally speaking, the lower the MAPE is and the higher the R-Square and Adjusted R-Square values are, the better the model is. The MAPE for this fitted model is calculated to be approximately 3.027 and Adjusted R-Square value is calculated to be approximately 0.94113. The fit statistics based on the residuals of the fitted model is shown in Table 7.9.

7.2.2. DA Price. The DA price is mainly decided by the demand and supply function. So, if the DA demand for the energy is forecasted to be high, then it is expected that the DA price will be higher. This happens because costlier units (units in the higher stacking order) will be used to meet higher demand. Using costlier units increases the price. However, as discussed in section four the DA price follows certain trend and cyclicality and therefore can be expressed with a time series model. The preliminary data analysis affirms that there exists a daily cycle for the price process.

The DA price process was initially modeled as a function of UCM components with a daily cycle and DA demand as a regressor variable. However, the model provided a lower Adjusted R-Square, higher MAPE and RMSE. Also, the AIC value was very high. The UCM model does not provide a good result as it missed many other variables such as seasonality, time of the day (peak/off peak) or week (weekday/weekend). Inclusion of a yearly cycle (seasonal UCM component) and the peak/off peak dummy variable yielded better results but we are not certain that the seasonal cycle component can be estimated accurately using only two years of data. Since the seasonal cycle is fitted as a stochastic term, the lack of data across many years may result in the complex seasonal component explaining the noise component in the data rather than the actual seasonal behavior. The evidence of seasonal components can be observed because the irregular component obtained from the fitted model had a variance that could not be statistically differentiated from zero. In simple terms, the model fitted the data almost perfectly, a clear indication of over-fitting.

Table 7.9. Fit Statistics Based on Residuals (DA Price)

Fit Statistics Based on Residuals	
Mean Squared Error (MSE)	6.23036
Root Mean Squared Error (RMSE)	2.49607
Mean Absolute Percentage Error (MAPE)	3.02790
R-Square	0.94114
Adjusted R-Square	0.94113

The DA price process could have been modeled with regression analysis using various key variables we indicated in our literature review. However, the biggest drawback of ordinary regression process in the context of electricity market is that residuals of ordinary regression analysis are considered to be independent of each other. This is a classical assumption of the ordinary regression analysis. The residuals obtained from such a regression fit showed clear autocorrelation. It was also learnt from the preliminary data analysis that the electricity price tends to be heteroscedastic. Therefore, a Generalized Autoregressive Conditional Heteroscedasticity or GARCH based model was fitted to the residual data to account for non constant error variance observed in the electricity market. The final model has the following variables. The variables under Regression Component refer to the ordinary regressors and the Heteroscedasticity and GARCH Component indicate the modeling of the error variance.

The proposed GARCH based regression model has the following components.

1. Regression Component
    a. Natural Logarithm of DA price for previous hour
    b. Natural Logarithm of DA price for previous day (this is one way to model cyclical behavior with a one-day period)
    c. DA Demand
    d. Dummy variable
        i. Peak/Off Peak
        ii. Weekday/Weekend
        iii. Seasonal (Summer/Winter/Shoulder months)
2. Heteroscedasticity and GARCH Component
    a. Mean of the GARCH model (denoted by ARCH (0) in Table 7.10).
    b. ARCH Coefficient (denoted by ARCH (1) in Table 7.10).
    c. GARCH component (denoted by GARCH(1,1) in Table 7.10).

So, the final DA Price model is given by:

$$\begin{aligned} DAP_t = a_1 * DAP_{t-1} + \ a_2 * DAP_{t-24} \ + a_3 DAD_t + a_4 * Dum_{peak/off-peak} \\ + a_5 * Dum_{weelday/weekend} + \ a_6 Sea\_Dum_1 + a_7 Sea\_Dum_2 \ + \varepsilon_t \end{aligned} \tag{38}$$

$$\varepsilon_t = \sqrt{h_t} e_t \tag{39}$$

$$e_t \sim N(0,1) \tag{40}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j}. \tag{41}$$

If p and q are set to be one, then equation (41) becomes

$$h_t = \omega + \alpha_i \varepsilon_{t-1}^2 + \gamma_j h_{t-1} \tag{42}$$

where,

DAP_t = Natural Logarithm of DA Price at time t

DAP_{t-1} = Natural Logarithm of DA Price at time $t-1$

DAP_{t-24} = Natural Logarithm of DA Price at time $t-24$

DAD_t = DA Demand for load at time t

$Dum_{peak/off-peak}$ = Dummy variable indicating Peak and Off Peak hours of the day

$Dum_{weekday/weekend}$ = Dummy variable indicating part of the week

Sea_Dum_1 = Dummy variable indicating first column of the Seasonal Dummy

Sea_Dum_2 = Dummy variable indicating second column of the Seasonal Dummy

a_i = Coefficients of Rgression for $i = 1,...,6$

ε_t = Error component at time t

ω = ARCH(0)

α_1 = ARCH(1)

γ_1 = GARCH(1,1).

The AIC is -16729.283, MSE is 0.03292 and the Total R-Square is computed to be 0.9976 for the fitted model. The final estimates for the parameters are shown in Table 7.10. The fitted model generated natural logarithm of price and natural logarithm of actual price are compared in Figure 7.10.

7.2.3. RT Time Load. RT Market is the balancing market. In RT, the market observes all the corrections and changes made in the DA clearing data based on the market dynamics such as weather. While weather is a primary explanatory variable in RT Load models, one can also identify certain trends or cycles in the load pattern. During the preliminary data analysis, it was observed that the pervious hour's load is correlated with the next hour's load. Therefore, the previous hour's load is included as an input to the model. The load is usually low in the morning and then it slowly increases reaching a peak at certain time during the day. The load is usually higher during the peak hours and lower during the off peak hours. Thus a daily cycle component is included in the RT Load model. The load shape also changes between weekdays and weekends. From these understandings, dummy variables for peak/off peak hours, and weekday/weekend are included in the final model. Similarly two seasonal dummies are also included to model the effects of summer, winter, and shoulder months. The dummy variables for different seasons are constructed in the same manner as was done earlier. The dummy variables work as explanatory or independent variable in the model.

Table 7.10. Final Estimates of the Parameters for DA Price

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Natural Logarithm of DA price at t_1	1	0.3747	0.003542	105.78	<.0001
Natural Logarithm of DA price at t_24	1	0.4844	0.002840	170.55	<.0001
DA Demand at t	1	0.007520	0.000159	47.16	<.0001
Seasonal Dummy variable: Column 1	1	0.000345	0.0000267	12.95	<.0001
Seasonal Dummy variable: Column 2	1	-0.0269	0.002951	-9.12	<.0001
Dummy variable for Peak/Off Peak	1	0.002132	0.000571	3.74	0.0002
Dummy variable for Weekday/Weekend	1	0.0326	0.002388	13.65	<.0001
ARCH(0)	1	0.006312	0.000120	52.64	<.0001
ARCH(1)	1	0.7991	0.0111	72.20	<.0001
GARCH(1,1)	1	0.0443	0.007410	5.98	<.0001

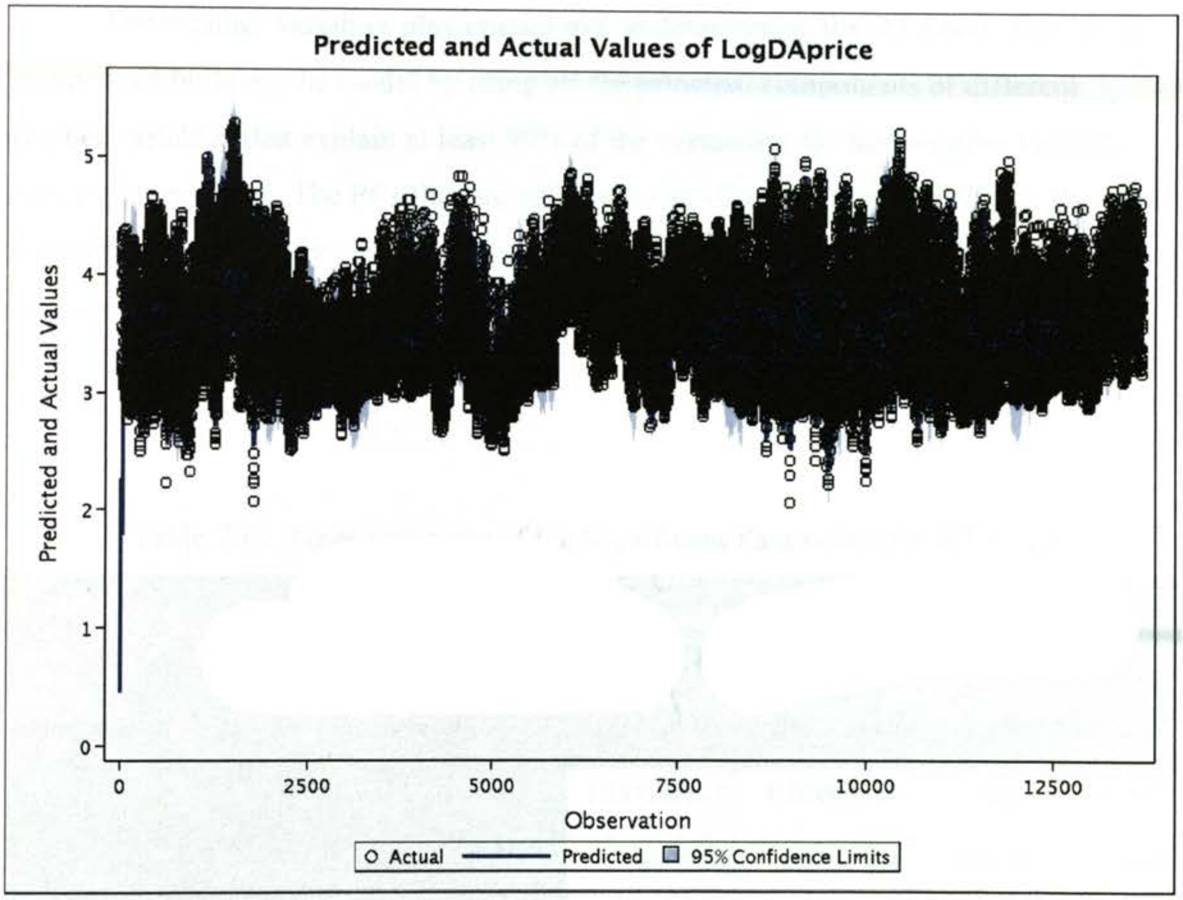

Figure 7.10. Predicted and Actual Values of Natural Logarithm of DA Price

The cycle component is modeled in the same fashion we showed for DA Demand. The summary statistics for the cycle component is shown in the Table 7.11 below. The estimates of regression coefficients for these variables are shown in the Table 7.12.

Table 7.11. Summary of Daily Cycles (RT Load)

Summary of Cycles							
Name	Type	Period	Frequency	Damping Factor	Final Amplitude	Cycle Variance	Error Variance
Cycle	Stationary	24.000	.26180	0.87379	4.08376	7.99615	1.89097

The weather variables play crucial role in determining the RT Load. This study commenced building the model by using all the principal components of different weather variables that explain at least 90% of the variability for that weather variable from different cities. The PCs that are either not significant or does not change the model fit statistics significantly are eliminated. The significant principal components and the regression coefficients are shown in the Table 7.12.

Table 7.12. Final Estimates of the Significant Parameters for RT Load

Final Estimates of the Free Parameters					
Component	**Parameter**	**Estimate**	**Approx Std Error**	**t Value**	**Approx Pr > |t|**
Irregular	Error Variance	1.257105E-7	0.00001330	0.01	0.9925
Daily Cycle	Damping Factor	0.87379	0.0037503	232.99	<.0001
Daily Cycle	Error Variance	1.89097	0.05323	35.52	<.0001
RT Load at t-1	Coefficient	0.85099	0.0039790	213.87	<.0001
Dummy variable for Peak/Off Peak	Coefficient	1.27766	0.05627	22.70	<.0001
Dummy variable for Weekday/Weekend	Coefficient	0.52823	0.08619	6.13	<.0001
PC1 for HDD	Coefficient	0.09071	0.0048918	18.54	<.0001
PC1 for CDD	Coefficient	0.01699	0.0017983	9.45	<.0001
Seasonal Dummy variable: Column 1	Coefficient	0.63336	0.12196	5.19	<.0001

Table 7.12 (Continued). Final Estimates of the Significant Parameters for RT Load

Component	Parameter	Estimate	Approx Std Error	t Value	Approx Pr > |t|
Seasonal Dummy variable: Column 2	Coefficient	-0.57764	0.14790	-3.91	<.0001
PC1 for Min Humidity	Coefficient	0.04022	0.0019126	21.03	<.0001
PC1 for Max Wind Speed	Coefficient	0.08826	0.0061096	14.45	<.0001
PC2 for Max Wind Speed	Coefficient	0.05141	0.0072407	7.10	<.0001
PC3 for Max Wind Speed	Coefficient	-0.04374	0.0096535	-4.53	<.0001
PC1 for Precipitation	Coefficient	-1.20751	0.11053	-10.92	<.0001
PC2 for Precipitation	Coefficient	-0.32274	0.13034	-2.48	0.0133
PC1 for Cloud Cover	Coefficient	-0.06455	0.01103	-5.85	<.0001
PC2 for Cloud Cover	Coefficient	-0.05767	0.01295	-4.45	<.0001

The final RT Load model in mathematical form is given by:

$$\begin{aligned} RTL_t = {} & \rho\psi_t + C_1 RTL_{t-1} + C_2 DUM_{Peak/Off-Peak} + C_3 DUM_{Weekday/Weekend} \\ & + C_4 DUM1_{season} + C_5 DUM2_{season} + C_6 PC1_{Min\_humidity} + \\ & + C_7 PC2_{Max\_wind} + C_8 PC3_{Max\_wind} + C_9 PC1_{Precipitation} + \\ & + C_{10} PC2_{Precipitation} + C_{11} PC1_{cloud} + C_{12} PC2_{cloud} + \\ & + C_{13} PC1_{Max\_wind} + Irreg \end{aligned} \tag{43}$$

where,

RTL_t = RT Load at time t

ρ = Damping factor from Unobserved Component Model (UCM)

ψ_t = Daily Cycle Compnent from UCM

RTL_{t-1} = RT Load at time $t-1$

$DUM_{Peak/Off-Peak}$ = Dummy variable representing Peak/Off - peak periods

$DUM_{Weekday/Weekend}$ = Dummy variable representing Weekend/Weekday

$DUM1_{season}$ = First Column of Dummy variable representing Season (Summer/ Winter/Shoulder)

$DUM2_{season}$ = First Column of Dummy variable representing Season (Summer/ Winter/Shoulder)

$PC1_{Min\_humidity}$ = First Pricipal Component of daily minimum humidity

$PC1_{Max\_wind}$ = First Pricipal Component of daily maximum wind speed

$PC2_{Max\_wind}$ = Second Pricipal Component of daily maximum wind speed

$PC3_{Max\_wind}$ = Third Pricipal Component of daily maximum wind speed

$PC1_{Precipitation}$ = First Pricipal Component of daily Precipitation

$PC2_{Precipitation}$ = Second Pricipal Component of daily Precipitation

$PC1_{cloud}$ = First Pricipal Component of daily cloud cover

$PC2_{cloud}$ = Second Pricipal Component of daily cloud cover

$C_i = C_1,...,C_{13}$ = Regression Coefficients

$Irreg$ = Irregular or error component of the UCM.

The model fit statistics for the RT Load model are given in the Table 7.13.

7.2.4. RT Price. Although the electricity price is determined by the demand and supply curve, there is possible gaming in the RT Market. RT Market which acts as a balancing market adjusts for possible outage, and extra load etc. and all these changes reflect in the RT price. To capture different market sentiments or how market could generate price spikes, physical variables that can be manipulated by some market participants are considered. Such variables can give a price signal. Apart from regular variables such as RT Load forecast, RT Price for the previous hours and other dummy variables, the following variables are introduced.

Table 7.13. Fit Statistics Based on Residuals

Fit Statistics Based on Residuals	
Mean Squared Error	2.02175
Root Mean Squared Error	1.42188
Mean Absolute Percentage Error	1.54150
Maximum Percent Error	11.43843
R-Square	0.98194
Adjusted R-Square	0.98194
Random Walk R-Square	0.70728

i) Net Scheduled Imports: This variable represents the total net interchanges import to the MISO (in GW) for a given hour for a particular market day. A higher import amount is an indication that there is not enough economic generation resource available in the market which has forced to import MWs. This could potentially hike the price in RT. Again, if some of the regular units do not clear or are not offered, it may be necessary to import from the interchange. If net import increases then speculators can take the chance to hike the price.

ii) Committed Emergency Resources (GW): This represents the total economic maximum energy committed by units across MISO footprint for emergency purpose. As the name suggests they are used during the emergency need for MWs. If this emergency commitment number is high, it is possible that the market is expecting higher turbulence in the RT and the speculators would take their chance to increase price.

iii) Generation Resource (Must Run): This indicates the MWs committed by must run units. These units are usually the nuclear and renewable energy generation units and are designated as must run. As the name suggests, the units would always clear unless there is a problem. The must run units are good indicator to judge whether the base load units are cleared or not. If there is a base load unit not working or a generation corporation does not offer its must run units, it is obvious that the market must use the MWs from higher order in the generation stacking thus by increasing the price of the energy.

The final RT Price model has the following mathematical form:

$$\begin{aligned}\ln\_RTP_t = a_1 * \ln\_\mathrm{RT}P_{t-1} + \; a_2 * RTL_t \; + a_3 * Sch\_imp_t + \\ + a_4 * Gen\_mustrun_t + a_5 * Dum_{peak/off-peak} + \\ + a_6 * Dum_{weelday/weekend} + \; a_7 Sea\_Dum_1 + \\ + a_8 Sea\_Dum_2 \; + \; \varepsilon_t\end{aligned} \tag{44}$$

$$\varepsilon_t = \sqrt{h_t} e_t \tag{45}$$

$$e_t \sim N(0,1) \tag{46}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j} \tag{47}$$

Setting p=1 and q=1 the equation (47) becomes,

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1} \tag{48}$$

where,

$\ln\_RTP_t$ = Natural Logarithm of RT Price at time t

$\ln\_RTP_{t-1}$ = Natural Logarithm of DA Price at time $t-1$

RTL_t = RT Load at time t

$Dum_{peak/off-peak}$ = Dummy variable indicating Peak and Off Peak hours of the day

$Dum_{weekday/weekend}$ = Dummy variable indicating part of the week

Sea_Dum_1 = Dummy variable indicating first column of the Seasonal Dummy

Sea_Dum_2 = Dummy variable indicating second column of the Seasonal Dummy

Sch_imp_t = Net Scheduled Import of MW

$Gen\_mustrun_t$ = Cleared Must Run Generation MW

Gen_Emg_t = Cleared MWs for emergency generation

a_i = Coefficients of Rgression for $i = 1,\ldots,6$

ε_t = Error component at time t

ω = Mean of the GARCH

α_1 = The ARCH Coefficient

γ_1 = The GARCH Coefficient.

Table 7.14 shows the final estimates of the RT price model. The fitted model generated natural logarithm of RT price and natural logarithm of actual RT price are compared in Figure 7.11. The preliminary data analysis, the DA Price for an hour was found to have some correlation with the RT Price for the same hour. The DA price also appears to be significant variable in the fitted model. This is not surprising because the DA market, in theory, acts as a forward market for the RT Market. RT market is the balancing market which takes care of the RT situation. DA market is the expected situation of the RT market based on the forecasted data. However, including this variable in the simulation model will make the model too much dependent on the forecasted or simulated data. Since the model should be as much self explanatory as possible, the DAP is not included in the final RTP model. Model's fit statistic does not change significantly by excluding this variable.

Table 7.14. Final Estimates of the RT Price

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > |t|
Natural Logarithm of RT price at t_1	1	0.6043	0.006911	87.44	<.0001
RT Load	1	0.0180	0.000717	25.08	<.0001
Net Scheduled Imports	1	-0.0262	0.002782	-9.41	<.0001
Generation Resource offered (Must Run)	1	0.005440	0.001022	5.32	<.0001
Generation Resource offered (Emergency)	1	0.0190	0.006220	3.06	0.0022
Seasonal Dummy variable: Column 1	1	-0.1398	0.008468	-16.51	<.0001
Seasonal Dummy variable: Column 2	1	-0.0534	0.008235	-6.49	<.0001
Dummy variable for Peak/Off Peak	1	0.0918	0.0111	8.23	<.0001
Dummy variable for Weekday/Weekend	1	-0.0426	0.009031	-4.72	<.0001
ARCH(0)	1	0.0703	0.002672	26.31	<.0001
ARCH(1)	1	0.1662	0.008897	18.69	<.0001
GARCH(1,1)	1	0.3330	0.0239	13.91	<.0001

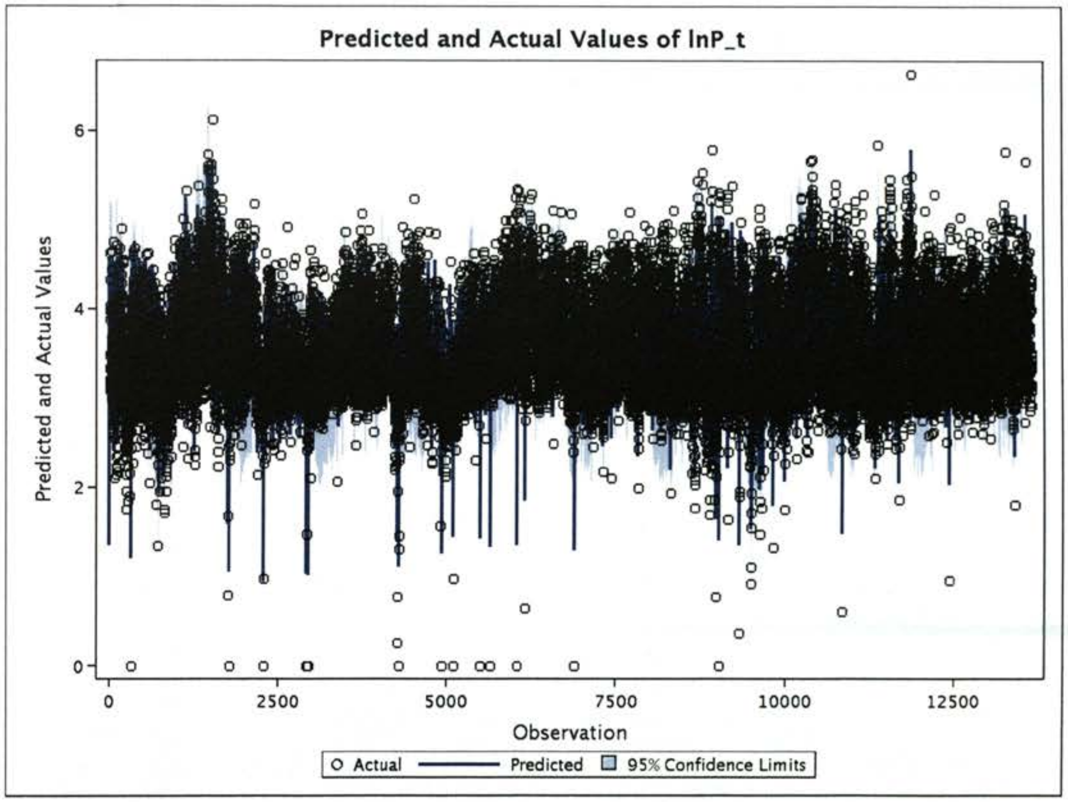

Figure 7.11. Predicted and Actual Values of Natural Logarithm of RTP

Virtuals, as traders believe in the industry, can influence the price. The general market belief is that if higher amount of the virtual supply is submitted in the market, then the speculators are expecting the RT price to be lower than the DA price. The cleared virtual offers or supplies must be bought back in RT market at RT LMP observed at the CP Node where the original offer was submitted and subsequently cleared. Clearly, the speculators with virtual supply award in DA market would gain from a lower price. This increases suspicion of market gaming by market leaders. A GARCH based model was fitted with cleared virtual supply and the difference between the cleared virtual bids and offers as two explanatory variables. Both the variables appear to be significant with small regression coefficients. However, these two variables were not included in the final proposed simulation model as it is difficult to model the cleared virtuals. Also, the virtual market is very new and do not have enough data and regulation in place to correctly simulate the bidding pattern by the participants. Virtuals are primarily used by the participants either to hedge or to speculate. The hedgers use virtual to financially hedge not only their generation offers or congestions, but also their power trading portfolio convoluted with financial products traded in the power market which are mostly structured products. The data is not publicly available unlike other financial commodity products traded in the different organized markets. This makes it even more difficult to model the reasons that influence the virtuals and determine how it should be modeled. The fit statistics for the fitted model does not significantly change when remove the virtuals are removed from the model.

8. SIMULATING THE FITTED MODEL AND TRADE ANALYSIS

This section shows how the models presented in section seven can be simulated to make a trading decision using either virtual bids or offers. First the fitted models for the demand, load and price processes are reiterated.

8.1. FITTED MODELS

8.1.1. DA Demand. The DA demand process for electricity is given by:

$$\breve{L}_t = I + \psi_t + \sum C_i R_i \tag{49}$$

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \rho \begin{bmatrix} Cos\lambda & Sin\lambda \\ -Sin\lambda & Cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} \nu_t \\ \nu_t^* \end{bmatrix} \tag{50}$$

where,

$\lambda = Period = \dfrac{2 * \pi}{24}$

$\breve{L}_t$ = DA Demand

I = Irregular component of UCM

ψ_t = Daily cycle component of UCM

C_i = Cofficient of regression for ith regressor

R_i = ith Regressors

ρ = Damping factor, $0 \le \rho \le 1$

ν_t and $\nu_t^* \sim IN(0, \sigma_\nu^2)$

σ_ν = Volatility of the cycle.

8.1.2. DA Price. The DA price process is given by the following set of equations.

$$DAP_t = a_1 * DAP_{t-1} + a_2 * DAP_{t-24} + a_3 DAD_t + a_4 * Dum_{peak/off-peak} + \\ + a_5 * Dum_{weelday/weekend} + a_6 Sea\_Dum_1 + \\ + a_7 Sea\_Dum_2 + \varepsilon_t \tag{51}$$

$$\varepsilon_t = \sqrt{h_t} e_t \tag{52}$$

$$e_t \sim N(0,1) \tag{53}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j}. \tag{54}$$

If p and q are set to be one, then the equation (54) becomes

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1} \tag{55}$$

where,

DAP_t = Natural Logarithm of DA price at time t

DAP_{t-1} = Natural Logarithm of DA price at time $t-1$

DAP_{t-24} = Natural Logarithm of DA price at time $t-24$

DAD_t = DA Demand for load at time t

$Dum_{peak/off-peak}$ = Dummy variable indicating peak and off peak hours

$Dum_{weekday/weekend}$ = Dummy variable indicating part of the week

Sea_Dum_1 = Dummy variable indicating first column of the seasonal dummy

Sea_Dum_2 = Dummy variable indicating second column of the seasonal dummy

a_i = Coefficients of regression for $i = 1,\ldots,6$

ε_t = Error component at time t

ω = The mean of the GARCH

α_1 = The ARCH component

γ_1 = The GARCH component

8.1.3. RT Load. The RT load process is given by the following equation.

$$\begin{aligned} RTL_t = {} & \rho\psi_t + C_1 RTL_{t-1} + C_2 DUM_{Peak/Off-Peak} + C_3 DUM_{Weekday/Weekend} + \\ & + C_4 DUM1_{season} + C_4 DUM1_{season} + C_5 DUM2_{season} + \\ & + C_6 PC1_{Min\_humidity} + C_7 PC2_{Max\_wind} + C_8 PC3_{Max\_wind} + \\ & + C_9 PC1_{\Pr ecipitation} + C_{10} PC2_{\Pr ecipitation} + C_{11} PC1_{cloud} + \\ & + C_{12} PC2_{cloud} + C_{13} PC1_{Max\_wind} + Irreg \end{aligned} \tag{56}$$

Where,

RTL_t = RT Load at time t

ρ = Damping factor from Unobserved Component Model (UCM)

ψ_t = Daily Cycle Compnent from UCM

RTL_{t-1} = RT Load at time $t-1$

$DUM_{Peak/Off-Peak}$ = Dummy variable representing Peak/Off - peak periods

$DUM_{Weekday/Weekend}$ = Dummy variable representing Weekend/Weekday

$DUM1_{season}$ = First Column of Dummy variable representing Season (Summer/Winter/Shoulder)

$DUM2_{season}$ = First Column of Dummy variable representing Season (Summer/Winter/Shoulder)

$PC1_{Min\_humidity}$ = First Pricipal Component of daily minimum humidity`.

8.1.4. RT Price. The RT price process is given by the following equations.

$$\begin{aligned} \ln\_RTP_t = {} & a_1 * \ln\_\mathrm{RT}P_{t-1} + a_2 * RTL_t + a_3 * Sch\_imp_t + a_4 * Gen\_mustrun_t \\ & + a_5 * Dum_{peak/off-peak} + a_6 * Dum_{weelday/weekend} + a_7 Sea\_Dum_1 \\ & + a_8 Sea\_Dum_2 + \varepsilon_t . \end{aligned} \tag{57}$$

$$\varepsilon_t = \sqrt{h_t} e_t \tag{58}$$

$$e_t \sim N(0,1) \tag{59}$$

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j} . \tag{60}$$

If p and q are set to be one, then the equation (60) becomes:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 h_{t-1} \tag{61}$$

Where,

$\ln\_RTP_t$ = Natural Logarithm of RT Price at time t

$\ln\_RTP_{t-1}$ = Natural Logarithm of DA Price at time $t-1$

RTL_t = RT Load at time t

$Dum_{peak/off-peak}$ = Dummy variable indicating Peak and Off Peak hours

$Dum_{weekday/weekend}$ = Dummy variable indicating part of the week

Sea_Dum_1 = Seasonal dummy variable 1

Sea_Dum_2 = Seasonal dummy variable 2

Sch_imp_t = Net Scheduled Import of MW

$Gen\_mustrun_t$ = Cleared Must Run Generation MW

Gen_Emg_t = Cleared MWs for emergency generation

a_i = Coefficients of Rgression for $i = 1,\ldots,6$

ε_t = Error component at time t

ω = Mean of GARCH

α_1 = The ARCH Component

γ_1 = The GARCH Component.

8.2. GENERATING SIMULATED DATA

The models are intended to run before one would submit the final bid and offers to respective ISO. Ideally the models would be run with the actual weather data. The same weather data cannot be used in estimating the models fitted in the previous chapter. Use of the same weather data will result in simulated series that may not reflect the weather variance one would expect from one year to the next. To overcome this drawback, the methodology described in Section 8.2.1 is used to generate simulated weather data that maintains the average seasonal patterns observed over the years, but still produces variability across different simulated series. This derived weather dataset would be called normalized weather database.

8.2.1. Normalizing Weather Data. The block bootstrap method is used to randomly pick a set of weather data from 10 years of actual weather data. The bootstrap methodology is sued on the residuals of the principal components of the weather variables. The bootstrapped data is constructed from a sample of 10 years of weather data for each of the seven stations. The bootstrap method is particularly helpful when there are enough observation available from the past. The block bootstrap maintains the autocorrelation structure that exists in the inter-day weather observations. Since the weather pattern does not change suddenly and daily weather patterns have significant similarities during a month, block bootstrap is an ideal sampling procedure to use.

First, the principal components of daily weather data are calculated based on the Eigen vectors computed during the model building. Then each yearly average PC was subtracted from its respective daily PC to get the residuals. Then the residual data was separated for each month for each year. The data from the same month are grouped into a set, indexed with the respective years. This procedure yields the sample space for a particular month. Then the block bootstrap methodology is conducted with a block size equal to the length of the month. A block of data was randomly selected form the bootstrapped data. The selected block of residual is then added back to the average of the respective PCs, to get bootstrapped PC for that month. Similar bootstrapped data was constructed for each month during the calendar year. The monthly bootstrapped data are combined to get the yearly data.

8.2.2. Modeling the Daily Cycle Component of the UCM Model. The following section shows the daily cycle of the UCM based on the following steps.

i) Estimate the angular frequency of the cycle. The angular frequency of the cycle is given by:

$$\lambda = \frac{2\pi}{Period} \tag{62}$$

For a daily cycle, the Period is set to 24 hours. Thus, set $Period = 24$

ii) Generate ν_t and ν_t^* are using $IN(0, \hat{\sigma}_\nu^2)$ process. The fitted model provided $\hat{\sigma}_\nu^2$

iii) Set initial condition (t=0) for ψ_t and ψ_t^*.

Set,

$$\psi_{t=0} = \alpha \qquad \text{and} \qquad \psi_{t=0}^* = \beta \tag{63}$$

Where,

$$\psi_t^2 + \psi_t^{*2} = \alpha^2 + \beta^2 \tag{64}$$

In practice, α and β should be estimated based on the previous day's data. For this case, the last day of the previous month's actual data is considered to estimate α and β.

iv) Set β as the difference between the maximum DA demand (or RT Load whichever is applicable) observed in the last day of the previous month and mean DA demand (or RT Load) observed in the last day of the previous month. Therefore,

$$\beta = Max - Mean \tag{65}$$

Where, Max = Maximum DA demand or RT Load whichever is applicable, observed in the last day of the previous month

$Mean$= Mean DA demand or RT Load whichever is applicable, observed in the last day of the previous month.

Now, set the α as follows:

$$\alpha = \sqrt{(HE1 - Mean)^2 - \beta^2} \tag{66}$$

Where, $HE1$ = DA demand or RT Load whichever is applicable, observed at the first hour of the last day of the previous month,

$Mean$= Mean DA demand or RT Load whichever is applicable, observed in the last day of the previous month,

β = As estimated above.

v) Simulate the cyclical component, ψ_t, using the following recursive formula. The model has already been discussed in Section 6. The damping coefficient, ρ, is estimated and taken from the fitted model.

$$\begin{bmatrix} \psi_t \\ \psi_t^* \end{bmatrix} = \hat{\rho} \begin{bmatrix} Cos\lambda & Sin\lambda \\ -Sin\lambda & Cos\lambda \end{bmatrix} \begin{bmatrix} \psi_{t-1} \\ \psi_{t-1}^* \end{bmatrix} + \begin{bmatrix} v_t \\ v_t^* \end{bmatrix}. \tag{67}$$

8.3. SIMULATING THE DA DEMAND, RT LOAD, DA PRICE AND RT PRICE PROCESSES

Once all the bootstrapped samples of principal component data for the time frame in consideration are generated, the DA Demand function given by equation (30) is used. The dummy variables are generated based on actual dates in 2007. It is important to understand the following constraints and assumptions for simulation purpose.

i) Physical properties of transmission such as congestion or transmission loss are not considered directly into the model. The model does not directly capture the plant outage or transmission line outage etc. which could potentially spike the price of electricity. The price fluctuations due to congestion, outages, and transmission loss are, however, addressed indirectly through the use of the conditional heteroscedastic (GARCH) formulation.

ii) GARCH based model presented in this dissertation is able to capture any volatility arising from dynamics between different commodity markets.

iii) The principal components of the climate variables shall capture the weather variation across the footprint.

iv) It is assumed that the hypothetical Genco/LSE must serve its native load from cheapest generation. The Genco follows a dynamic hedging strategy involving long term (LT) hedge, short term (ST) hedge and then it tries to manage the risk in DA/RT market using virtuals. In real life the hedge plan may be more complicated with the usage of different types of structured derivative products. A simple case where the generation company is able to produce and market the load is considered in this dissertation. It does not need to serve the ancillary services market, nor does it have any regulatory instructions on how much it needs to sell.

v) Demand bids or generation offers made by the LSE/Genco completely clear in the DA market.

vi) All the generation companies in the market make offers based on the "cost plus" policy and there is no foul playing in the market. No gaming occurs in the market.

vii) The virtual bids and offers made by our market participants clear in the DA market. It is assumed that the market participant's bid or offer amount equal 1 MW and it gets cleared.

viii) All the participants follow MISO rules.

ix) The market participant meets the MISO's credit limit to trade virtuals.

x) The Genco owns a must run/base load unit. If the unit ramps down or trips off, the generation stack is affected and it reflects in the amounts cleared by must run (usually in decreased amount).

xi) Since the MISO imposes a cap of $1000/MWh on price bids, the simulation also imposes a cap of $1000/MWh.

xii) The bootstrapped data based on past 10 years of weather data produces a possible weather pattern for the region.

8.4. SIMULATION RESULTS AND TRADING ANALYSIS

8.4.1. Simulation Results. After the weather data preparation is done, the fitted models are simulated. Since price models have demand or load as input, the demand and load data are generated first. Data generated by all the four series—RTL, DAD, RTP and DAP are used to test the performance of different strategies. Each process was simulated for 1000 times. Then performance statistics for each strategy is computed based on the 1,000 runs. Figure 8.1 and Figure 8.2 shows the simulated DAP and RTP. Tables 8.1, 8.2, 8.3 and 8.4 show the monthly and hourly average simulated DAP and RTP. Please note that usually the peak hours are the operating hours between HE7 and HE 22 for Eastern Standard Time (or HE8 through HE23 during the day light savings months) during weekdays and non-holidays. However, in the tables showing statistics for the shoulder and winter months, you will note that both HE 7 and HE 8 are recognized as peak hours. This is because day light savings time shift that happens in those months.

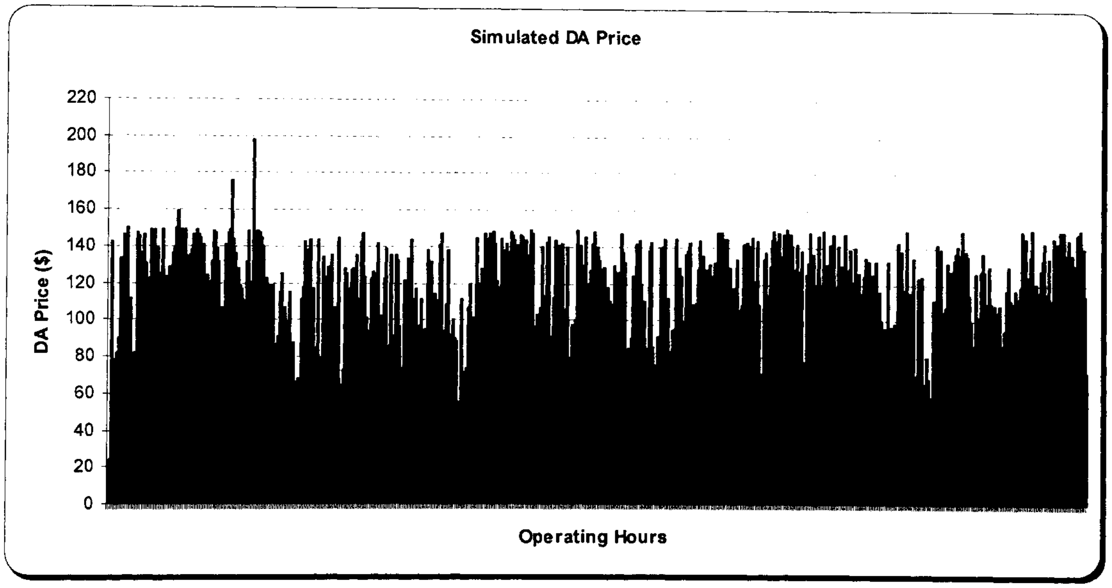

Figure 8.1. Simulated DA LMP

8.4.2. Trading Performance Analysis. Market participants use various forecasting methods to predict DAP and RTP and based on these forecast values determine whether to make a virtual bid or a virtual offer. The effectiveness of their bidding strategies will depend on the accuracy of their forecasting models. The types of forecasting techniques used by market participants range from neural networks to statistical time series models as well as hybrid strategies that incorporate historical data, weather forecasts, and expert opinion. Some of these models are highly proprietary and are not available for academic investigations such as this doctoral study. Others use variables, such as information about unit breakdowns or congestion, which are not available to us. Thus, simulating the actual forecasting processes used by the various market participants is not feasible. Therefore, two alternative methods are applied to study the performance of various strategies. The first method is to assume that the market participants have perfect prediction models with zero error. While this is not true in practice, the results obtained from this method will yield an upper bound for the relative profits one can make in the virtual electricity market. The second method is to assume that the predictive models used by the participants have a certain error rate (say 5% error) and perturb the actual DAP and RTP by this amount and use the error added values to make a decision on whether or not to make a virtual bid (or an offer).

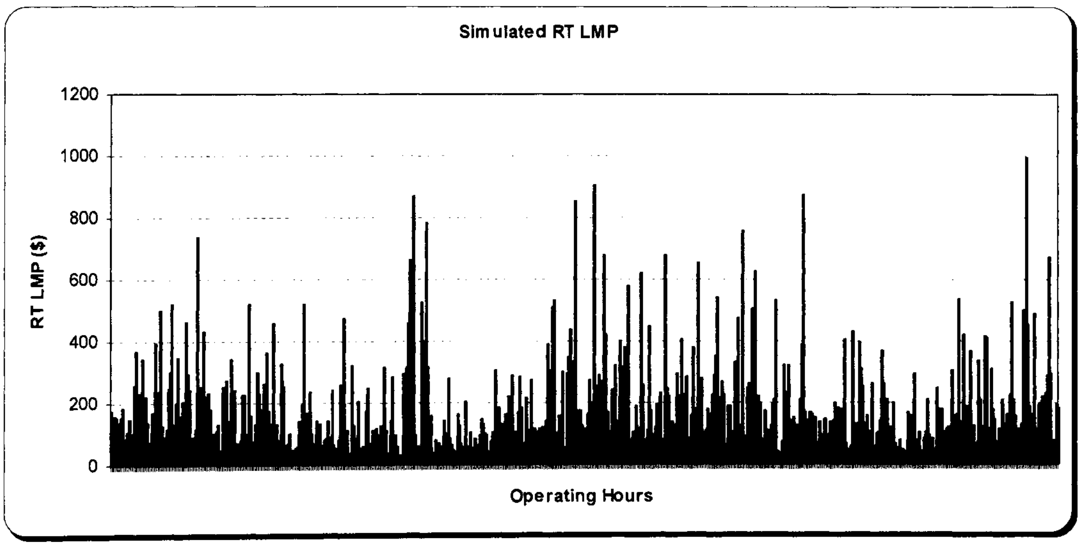

Figure 8.2. Simulated RT LMP

A market participant who trades only virtual bids if the forecast data shows DAP<RTP and trades virtual offers if the forecast data shows DAP>RTP is considered. Assuming that they have perfect forecasts (with this assumption, forecasted DAP is equal to the actual DAP and forecasted RTP is equal to the actual RTP). For virtual bid trader, the profit and loss (P&L) calculated based on the simulated data are shown in Tables 8.5, 8.6, and 8.7. P&L from virtual offer trading is shown in Tables 8.8, 8.9 and 8.10.

Table 8.1. Monthly Average Simulated DAP and RTP

	Average of DAP		Average of RTP	
Month	Off Peak	Peak	Off Peak	Peak
Janurary	$ 53.54	$ 56.56	$ 60.86	$ 83.54
February	$ 57.89	$ 57.11	$ 62.66	$ 65.53
March	$ 37.86	$ 37.93	$ 44.86	$ 44.85
April	$ 37.92	$ 49.24	$ 37.90	$ 59.11
May	$ 38.37	$ 49.14	$ 32.34	$ 50.34
June	$ 46.67	$ 56.29	$ 60.22	$ 66.93
July	$ 48.79	$ 48.97	$ 59.05	$ 83.09
August	$ 53.68	$ 61.73	$ 77.28	$ 75.16
September	$ 46.75	$ 59.12	$ 56.97	$ 85.07
October	$ 37.33	$ 47.59	$ 42.46	$ 55.93
November	$ 38.11	$ 52.85	$ 40.95	$ 50.76
December	$ 56.78	$ 58.76	$ 62.21	$ 97.26

Table 8.2. Hourly Average Simulated DAP and RTP for Shoulder Months

		Average of DAP		Average of RTP	
Season	HE	Off Peak	Peak	Off Peak	Peak
Shoulder Months	1	$ 40.29		$ 46.43	
	2	$ 36.90		$ 41.38	
	3	$ 37.69		$ 41.47	
	4	$ 34.38		$ 53.26	
	5	$ 35.07		$ 51.00	
	6	$ 40.94		$ 47.95	
	7	$ 41.64	$ 48.84	$ 41.57	$ 44.96
	8	$ 35.96	$ 52.03	$ 37.01	$ 47.58
	9	$ 40.13	$ 46.10	$ 34.78	$ 40.63
	10	$ 42.25	$ 47.19	$ 33.64	$ 56.04
	11	$ 38.40	$ 50.20	$ 41.14	$ 51.69
	12	$ 51.34	$ 50.77	$ 46.30	$ 51.92
	13	$ 45.75	$ 49.74	$ 39.38	$ 57.33
	14	$ 31.98	$ 42.80	$ 38.49	$ 54.32
	15	$ 36.62	$ 41.61	$ 32.10	$ 52.14
	16	$ 34.65	$ 43.71	$ 28.99	$ 58.05
	17	$ 41.31	$ 48.09	$ 24.77	$ 61.75
	18	$ 32.81	$ 45.68	$ 28.60	$ 69.23
	19	$ 39.46	$ 50.18	$ 31.32	$ 57.16
	20	$ 50.48	$ 51.21	$ 36.67	$ 61.12
	21	$ 44.30	$ 52.06	$ 33.24	$ 58.76
	22	$ 44.61	$ 45.93	$ 37.73	$ 60.55
	23	$ 44.64	$ 64.94	$ 53.75	$ 68.46
	24	$ 42.17		$ 51.00	

Table 8.3. Hourly Average Simulated DAP and RTP for Summer Months

		Average of DAP		Average of RTP	
Season	HE	Off Peak	Peak	Off Peak	Peak
Summer Months	1	$ 50.14		$ 78.51	
	2	$ 46.73		$ 76.60	
	3	$ 42.29		$ 66.78	
	4	$ 42.63		$ 75.16	
	5	$ 44.28		$ 67.93	
	6	$ 53.44		$ 67.38	
	7	$ 49.40	$ 53.65	$ 65.13	$ 76.61
	8	$ 47.03	$ 49.11	$ 52.49	$ 73.54
	9	$ 51.65	$ 44.91	$ 47.14	$ 72.20
	10	$ 47.15	$ 49.49	$ 47.28	$ 68.24
	11	$ 45.97	$ 60.05	$ 48.72	$ 80.54
	12	$ 58.17	$ 66.97	$ 49.64	$ 72.34
	13	$ 51.67	$ 53.97	$ 72.97	$ 73.60
	14	$ 52.65	$ 59.56	$ 46.37	$ 79.60
	15	$ 51.97	$ 57.70	$ 59.58	$ 86.35
	16	$ 56.59	$ 68.12	$ 40.07	$ 86.88
	17	$ 62.45	$ 67.37	$ 39.35	$ 74.93
	18	$ 43.58	$ 57.93	$ 44.23	$ 78.72
	19	$ 49.89	$ 55.61	$ 41.92	$ 75.62
	20	$ 50.06	$ 51.52	$ 43.64	$ 96.27
	21	$ 59.08	$ 56.11	$ 42.35	$ 98.51
	22	$ 46.42	$ 54.95	$ 39.88	$ 98.75
	23	$ 56.90		$ 82.23	
	24	$ 51.14		$ 74.66	

Table 8.4. Hourly Average Simulated DAP and RTP for Winter Months

		Average of DAP		Average of RTP	
Season	HE	Off Peak	Peak	Off Peak	Peak
Winter Months	1	$ 49.55		$ 61.84	
	2	$ 48.44		$ 54.09	
	3	$ 48.33		$ 63.34	
	4	$ 53.10		$ 59.32	
	5	$ 49.20		$ 55.90	
	6	$ 53.37		$ 64.93	
	7	$ 50.15	$ 26.15	$ 56.69	$ 17.97
	8	$ 43.57	$ 50.88	$ 67.76	$ 67.98
	9	$ 45.04	$ 53.09	$ 67.96	$ 75.51
	10	$ 48.88	$ 55.17	$ 70.70	$ 81.29
	11	$ 54.85	$ 53.84	$ 73.88	$ 84.06
	12	$ 60.32	$ 59.69	$ 63.52	$ 80.74
	13	$ 56.69	$ 66.53	$ 52.26	$ 63.06
	14	$ 64.81	$ 61.93	$ 43.31	$ 66.05
	15	$ 38.07	$ 46.28	$ 35.92	$ 66.89
	16	$ 38.23	$ 49.52	$ 40.20	$ 69.49
	17	$ 34.20	$ 52.34	$ 32.22	$ 69.58
	18	$ 53.93	$ 51.03	$ 36.27	$ 83.62
	19	$ 62.47	$ 55.62	$ 39.65	$ 83.87
	20	$ 60.19	$ 57.82	$ 51.17	$ 79.91
	21	$ 57.37	$ 64.45	$ 54.25	$ 77.84
	22	$ 61.07	$ 60.79	$ 45.86	$ 68.25
	23	$ 61.10	$ 62.46	$ 44.91	$ 70.50
	24	$ 55.75		$ 64.75	

Table 8.5. Seasonal Average P&L for 1MW of Virtual Bid

	Peak/Off-peak		
Seasonal Average	**Off Peak**	**Peak**	**Total Average**
Shoulder Months	$ 19.54	$ 27.26	$ 23.21
Summer Months	$ 33.20	$ 40.83	$ 36.68
Winter Months	$ 23.63	$ 36.07	$ 29.37

Table 8.6. Monthly Average P&L for 1MW of Virtual Bid

	Peak/Off-peak		
Monthly	**Off Peak**	**Peak**	**Total Average**
January	$ 26.15	$ 42.51	$ 33.89
February	$ 26.33	$ 30.69	$ 28.41
March	$ 19.49	$ 21.28	$ 20.34
April	$ 16.90	$ 31.26	$ 23.60
May	$ 11.47	$ 23.16	$ 17.00
June	$ 31.03	$ 32.66	$ 31.79
July	$ 29.30	$ 46.15	$ 36.91
August	$ 41.18	$ 34.16	$ 37.71
September	$ 29.80	$ 43.02	$ 35.38
October	$ 18.98	$ 28.33	$ 23.61
November	$ 15.87	$ 19.82	$ 17.71
December	$ 26.09	$ 51.45	$ 37.01

Errors in weather forecast can cause significant error in the load forecast models. Load forecast error due to weather forecast error could be in the range of 8-10% (Atalo and Smith, 2004). This load forecast error could swing the predicted DA and RT price creating price risk for the trader. A market participant can use virtual bid and offer to protect itself from such price risk. In the following sections, the price outcomes are changed from the simulation generated data (simulation generated price data are considered the actual market values) by 5% to analyze the performance of the virtual trading strategies. Next the load and demand data inputs are changed by 10% to analyze the performance of the virtual trading strategies.

Table 8.7. Hourly Average P&L for 1MW of Virtual Bid

	Peak/Off-peak		
HE	Off Peak	Peak	Total Average
1	$ 28.82		$ 28.82
2	$ 27.54		$ 27.54
3	$ 26.68		$ 26.68
4	$ 32.60		$ 32.60
5	$ 27.87		$ 27.87
6	$ 27.36		$ 27.36
7	$ 23.11	$ 26.89	$ 24.84
8	$ 25.35	$ 29.10	$ 27.97
9	$ 22.73	$ 28.48	$ 26.75
10	$ 18.93	$ 33.92	$ 29.40
11	$ 24.10	$ 33.35	$ 30.56
12	$ 21.63	$ 31.28	$ 28.38
13	$ 25.75	$ 29.10	$ 28.09
14	$ 16.34	$ 30.86	$ 26.49
15	$ 15.79	$ 32.46	$ 27.44
16	$ 10.54	$ 33.03	$ 26.25
17	$ 8.00	$ 31.27	$ 24.26
18	$ 11.40	$ 42.68	$ 33.26
19	$ 11.01	$ 36.26	$ 28.65
20	$ 15.05	$ 42.93	$ 34.53
21	$ 16.37	$ 37.23	$ 30.94
22	$ 12.72	$ 36.32	$ 29.21
23	$ 30.63	$ 28.50	$ 30.11
24	$ 29.13		$ 29.13
Grand Total	$ 24.40	$ 33.48	$ 28.63

Table 8.8. Monthly Average P&L for 1MW of Virtual Offer

	Peak/Off-peak		
Month	**Off Peak**	**Peak**	**Grand Total**
January	$ 19.53	$ 15.53	$ 17.60
February	$ 21.56	$ 22.27	$ 21.90
March	$ 12.50	$ 14.36	$ 13.38
April	$ 16.92	$ 21.40	$ 19.01
May	$ 17.50	$ 21.97	$ 19.62
June	$ 17.47	$ 22.02	$ 19.59
July	$ 19.04	$ 12.03	$ 15.87
August	$ 17.58	$ 20.74	$ 19.14
September	$ 19.58	$ 17.07	$ 18.52
October	$ 13.85	$ 19.99	$ 16.89
November	$ 13.03	$ 21.90	$ 17.17
December	$ 20.60	$ 12.96	$ 17.32
Grand Total	**$ 17.45**	**$ 18.55**	**$ 17.96**

Table 8.9. Hourly Average P&L for 1MW of Virtual Offer

	Peak/Off-peak		
HE	Off Peak	Peak	Grand Total
1	$ 15.09		$ 15.09
2	$ 16.32		$ 16.32
3	$ 14.03		$ 14.03
4	$ 14.49		$ 14.49
5	$ 13.06		$ 13.06
6	$ 17.15		$ 17.15
7	$ 17.01	$ 20.70	$ 18.70
8	$ 15.49	$ 19.40	$ 18.23
9	$ 18.52	$ 16.78	$ 17.30
10	$ 15.14	$ 17.00	$ 16.44
11	$ 16.02	$ 17.82	$ 17.28
12	$ 25.05	$ 22.61	$ 23.34
13	$ 24.39	$ 22.14	$ 22.81
14	$ 22.84	$ 19.65	$ 20.60
15	$ 16.31	$ 14.17	$ 14.82
16	$ 16.50	$ 15.76	$ 15.98
17	$ 21.38	$ 17.95	$ 18.98
18	$ 18.85	$ 16.87	$ 17.47
19	$ 24.04	$ 19.13	$ 20.61
20	$ 25.30	$ 20.45	$ 21.91
21	$ 26.25	$ 19.53	$ 21.56
22	$ 22.31	$ 16.82	$ 18.48
23	$ 19.69	$ 20.82	$ 19.96
24	$ 16.46		$ 16.46

Table 8.10. Seasonal Average P&L for 1MW of Virtual Offer

	Peak/Off-peak		
Season	Off Peak	Peak	Grand Total
Shoulder	$ 15.65	$19.92	$ 17.68
Summer	$ 18.77	$16.73	$ 17.84
Winter	$ 18.67	$18.15	$ 18.43

8.4.2.1. Changing price data by 5%. Changing the price to incorporate possible prediction errors of the DAP and RTP would show how the virtual trading are impacted when traders use forecast data with error to make trading decisions. The 5% error in the price data was chosen arbitrarily. This error added data is called "forecast data." For the four different cases shown in the following sections, the market participant trades virtual bids if the forecast data shows DAP<RTP and trades virtual offers if the forecast data shows DAP>RTP. For each case under this scenario, the trading performance has been discussed below.

8.4.2.1.1. Case 1: Forecast RTP is 5% higher and forecast DAP is 5% lower than the true values. For virtual bid, the profit and loss (P&L) is calculated based on the simulated data are shown in Tables 8.11, and 8.12. P&L from virtual offer trading is shown in Tables 8.13, and 8.14. The virtual bids make profit approximately 45.86% of the time and approximately 54.13% of the times virtual offers make profit. Profits from the virtual bids are largest during the summer months followed by winter and shoulder months (for both peak and off peak hours). Virtual offers are most profitable during peak hours of the shoulder months. However, during off peak hours summer months seems to be mort profitable.

Table 8.11. Case 1: Monthly Average P&L for 1MW of Virtual Bid

	Peak/Off-peak	
Month	**Off Peak**	**Peak**
January	$ 29.25	$ 47.09
February	$ 29.58	$ 34.13
March	$ 21.81	$ 23.66
April	$ 18.79	$ 34.39
May	$ 13.07	$ 25.58
June	$ 34.31	$ 36.17
July	$ 32.38	$ 50.86
August	$ 45.52	$ 38.36
September	$ 32.77	$ 47.81
October	$ 21.21	$ 31.17
November	$ 18.00	$ 22.46
December	$ 29.38	$ 57.18
Grand Total	$ 27.19	$ 37.16

Table 8.12. Case 1: Seasonal Average P&L for 1MW of Virtual Bid

	Peak/Off-peak	
Season	**Off Peak**	**Peak**
Shoulder	$ 21.81	$ 30.11
Summer	$ 36.63	$ 45.38
Winter	$ 26.57	$ 40.17

Table 8.13. Case 1: Monthly Average P&L for 1MW of Virtual Offer

	Peak/Off-peak	
Month	**Off Peak**	**Peak**
January	$ 16.21	$ 13.10
February	$ 18.78	$ 19.58
March	$ 10.68	$ 12.60
April	$ 15.02	$ 19.11
May	$ 15.57	$ 19.41
June	$ 15.41	$ 19.37
July	$ 16.73	$ 10.13
August	$ 15.37	$ 18.09
September	$ 17.37	$ 14.65
October	$ 12.09	$ 17.66
November	$ 11.21	$ 19.37
December	$ 18.01	$ 10.89
Grand Total	$ 15.23	$ 16.20

Table 8.14. Case 1: Seasonal Average P&L for 1MW of Virtual Offer

	Peak/Off-peak	
Season	**Off Peak**	**Peak**
Shoulder	$ 13.76	$ 17.60
Summer	$ 16.53	$ 14.40
Winter	$ 16.05	$ 15.71

8.4.2.1.2. Case 2: Forecast RTP is 5% is lower and forecast DAP is 5% higher than the true values. For virtual bids, the profit is calculated based on the simulated data are shown in Tables 8.15, and 8.16. Profits from virtual offer trading are shown in Tables 8.17, and 8.18. The virtual bids make profit approximately 46.67% of the time and approximately 53.32% of the times virtual offers make profit. Profits from the virtual bids are higher during the winter and summer followed by the shoulder months (for peak hours). The virtual offers are most profitable during peak hours of the shoulder months and during off peak hours of summer and winter months.

Table 8.15. Case 2: Seasonal Average P&L for 1MW of Virtual Bid

	Peak/Off-peak	
Season	**Off Peak**	**Peak**
Shoulder	$ 24.53	$ 17.68
Summer	$ 36.49	$ 21.19
Winter	$ 32.23	$ 21.16

Table 8.16. Case 2: Monthly Average P&L for 1MW of Virtual Bid

	Peak/Off-peak	
Month	**Off Peak**	**Peak**
January	$ 23.26	$ 38.26
February	$ 23.29	$ 27.39
March	$ 17.32	$ 19.02
April	$ 15.10	$ 28.23
May	$ 9.95	$ 20.82
June	$ 27.93	$ 29.27
July	$ 26.37	$ 41.60
August	$ 37.10	$ 30.19
September	$ 26.96	$ 38.48
October	$ 16.92	$ 25.63
November	$ 13.93	$ 17.44
December	$ 22.89	$ 45.95
Grand Total	$ 21.77	$ 29.99

Table 8.17. Case 2: Seasonal Average P&L for 1MW of Virtual Offer

	Peak/Off-peak	
Season	**Off Peak**	**Peak**
Shoulder	$ 17.68	$ 22.34
Summer	$ 21.19	$ 19.26
Winter	$ 21.16	$ 20.82

Table 8.18. Case 2: Monthly Average P&L for 1MW of Virtual Offer

	Peak/Off-peak	
Month	**Off Peak**	**Peak**
January	$ 21.67	$ 18.28
February	$ 24.54	$ 25.11
March	$ 14.46	$ 16.24
April	$ 18.92	$ 23.78
May	$ 19.52	$ 24.60
June	$ 19.72	$ 24.79
July	$ 21.50	$ 14.08
August	$ 20.05	$ 23.61
September	$ 21.93	$ 19.74
October	$ 15.78	$ 22.47
November	$ 15.05	$ 24.71
December	$ 23.42	$ 15.26
Grand Total	$ 19.74	$ 21.09

8.4.2.1.3. Case 3: Both forecast RTP and forecast DAP are 5% lower than the true values. For virtual bid, the profit calculated based on the simulated data are shown in Tables 8.19, and 8.20. Profits from Virtual offer trading is shown in Tables 8.21 and 8.22. The virtual bids make profit approximately 50.60% of the time and approximately 49.39% of the times virtual offers make profit. Profits from the virtual bids are higher during the summer months followed by winter and shoulder months (for peak hours). However, virtual offers are most profitable during peak hours of the shoulder months and during off peak hours of summer and winter months.

Table 8.19. Case 3: Monthly Average P&L for 1MW of Virtual Bid

	Peak/Off-peak	
Month	Off Peak	Peak
January	$ 24.84	$ 40.38
February	$ 25.02	$ 29.15
March	$ 18.52	$ 20.21
April	$ 16.05	$ 29.70
May	$ 10.90	$ 22.01
June	$ 29.48	$ 31.02
July	$ 27.83	$ 43.84
August	$ 39.12	$ 32.45
September	$ 28.31	$ 40.87
October	$ 18.03	$ 26.92
November	$ 15.07	$ 18.83
December	$ 24.72	$ 48.88
Grand Total	$ 23.17	$ 31.81

Table 8.20. Case 3: Seasonal Average P&L for 1MW of Virtual Bid

	Peak/Off-peak	
Season	Off Peak	Peak
Shoulder	$ 18.57	$ 25.90
Summer	$ 31.54	$ 38.79
Winter	$ 22.43	$ 34.27

Table 8.21. Case 3: Seasonal Average P&L for 1MW of Virtual Offer

	Peak/Off-peak	
Season	Off Peak	Peak
Shoulder	$ 14.87	$ 18.92
Summer	$ 17.83	$ 15.89
Winter	$ 17.57	$ 17.24

8.4.2.1.4. Case 4: Both forecast RTP and forecast DAP are 5% higher than the true values. For virtual bid, the profit calculated based on the simulated data are shown in Tables 8.23, and 8.24. Profits from virtual offer trading are shown in Tables

8.25, and 8.26. The virtual bids make profit approximately 50.60% of the time and approximately 49.39% of the times virtual offers make profit. Profits from the virtual bids are higher during the summer months followed by winter and shoulder months (for peak hours). However, virtual offers are most profitable during peak hours of the shoulder months and during off peak hours of summer and winter months.

Table 8.22. Case 3: Monthly Average P&L for 1MW of Virtual Offer

	Peak/Off-peak	
Month	**Off Peak**	**Peak**
January	$ 17.89	$ 14.75
February	$ 20.48	$ 21.15
March	$ 11.87	$ 13.64
April	$ 16.07	$ 20.33
May	$ 16.63	$ 20.87
June	$ 16.60	$ 20.92
July	$ 18.09	$ 11.42
August	$ 16.70	$ 19.70
September	$ 18.60	$ 16.22
October	$ 13.16	$ 18.99
November	$ 12.38	$ 20.81
December	$ 19.57	$ 12.31
Grand Total	$ 16.53	$ 17.62

Table 8.23. Case 4: Seasonal Average P&L for 1MW of Virtual Bid

	Peak/Off-peak	
Season	**Off Peak**	**Peak**
Shoulder	$ 20.52	$ 28.63
Summer	$ 34.86	$ 42.87
Winter	$ 24.79	$ 37.88

8.4.2.2. Net long position and forecast RT load < forecast DA demand and/or forecast RT LMPs < forecast DA LMP. The forecasted price and load data are compared for the conditions mentioned in the case title. In this strategy, the trader (who is long in the market) buys the forecasted load with a demand bid, and uses the virtual offer to sell back part of the load. If the forecasted RT Load is greater than the forecasted DA demand or the forecasted RT LMP is smaller than the forecasted DA LMP, then the strategy is to use the virtual offer to sell back part of the load. The profit and loss (P&L) associated with virtual offer strategy for 1MW of virtual offer cleared is calculated based on simulated DAP and RTP. The P&L results are shown in Figure 8.3. Approximately 80.33% of the times, the strategy yield a profitable position.

Table 8.24. Case 4: Monthly Average P&L for 1MW of Virtual Bid

	Peak/Off-peak	
Month	**Off Peak**	**Peak**
January	$ 27.46	$ 44.63
February	$ 27.65	$ 32.22
March	$ 20.47	$ 22.34
April	$ 17.74	$ 32.83
May	$ 12.05	$ 24.32
June	$ 32.58	$ 34.29
July	$ 30.76	$ 48.46
August	$ 43.24	$ 35.87
September	$ 31.29	$ 45.18
October	$ 19.93	$ 29.75
November	$ 16.66	$ 20.81
December	$ 27.33	$ 54.03
Grand Total	$ 25.61	$ 35.16

Table 8.25: Case 4: Seasonal Average P&L for 1MW of Virtual Offer

	Peak/Off-peak	
Season	**Off Peak**	**Peak**
Shoulder	$ 16.43	$ 20.91
Summer	$ 19.71	$ 17.56
Winter	$ 19.42	$ 19.05

Table 8.26. Case 4: Monthly Average P&L for 1MW of Virtual Offer

	Peak/Off-peak	
Month	Off Peak	Peak
January	$ 19.77	$ 16.30
February	$ 22.64	$ 23.38
March	$ 13.12	$ 15.07
April	$ 17.76	$ 22.47
May	$ 18.38	$ 23.07
June	$ 18.34	$ 23.12
July	$ 19.99	$ 12.63
August	$ 18.46	$ 21.77
September	$ 20.56	$ 17.93
October	$ 14.54	$ 20.99
November	$ 13.69	$ 23.00
December	$ 21.63	$ 13.61
Grand Total	$ 18.26	$ 19.48

8.4.2.3. Market gaming. The market participant tries to manipulate the market condition by decreasing its demand bids, and at the same time offering full generation resources. It also uses virtual bids during the same hours. In this case, the DA demand is assumed to decrease by 10% because of the lower DA Demand bid by the participant. With this strategy, the market participant plays a speculative game in which their strategy causes the DA price to go down. However, in RT the load increases causing a price spike. This speculative trade will take the advantage of this price manipulation by using a virtual bid. It is assumed that the trader engages this strategy everyday during the year irrespective of what the models says about possible price deviation. The strategy is evaluated by using the simulated dataset. The P&L is also calculated based on simulated DAP and RTP. The simulation for this case uses the assumption that the DAD will decrease by 10% because of lowered DA demand bid by the participant. The P&L results are shown in Figure 8.3. The net P&L during the year from this strategy is $17, 6374.56. The maximum P&L from 1MW cleared virtual offer was $99.36 and minimum was $127.43 and the average P&L was $20.19. Although it seems that there were higher losses compared to daily profits, there were more profitable trades, which make the net P&L to be high profit. The simulation also shows that 75% of the times the strategy would yield a profitable position.

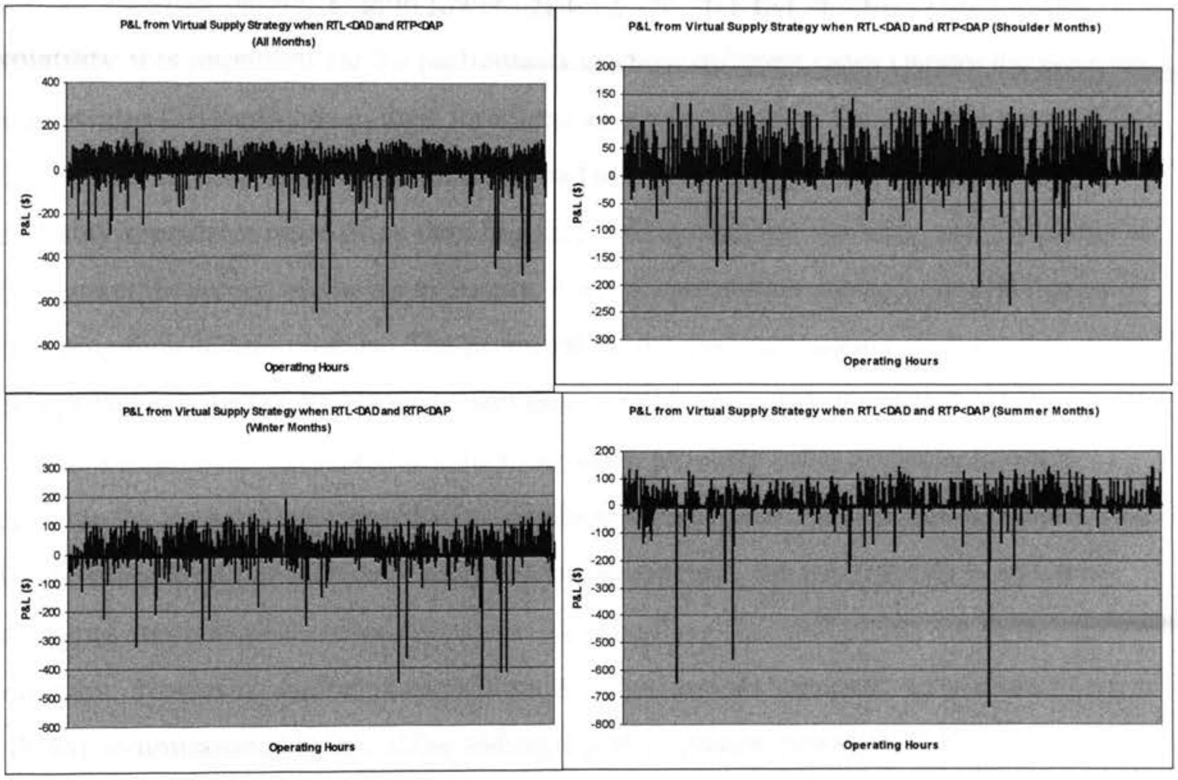

Figure 8.3. P&L from Virtual Supply Strategy when RTL<DAD and RTP<DAP

8.5. DISCUSSION

From the simulation results, it is inferred that the virtual bids are most profitable during the summer and virtual offer strategies are most profitable during the shoulder months. In summer months, it is often noticed that the RT price spikes up due congestion and weather related reasons. Summer months tend to be more volatile, at least in the past two years when. Therefore, the virtual bids were most profitable during the summer months. On the other hand shoulder months tend to be flat in terms of load. This makes the RT price not to fluctuate too much except when there is heaving congestion or other physical problems in the transmission line. Therefore, virtual offers which takes advantage when the DA price is higher than RT price, was more profitable during the shoulder months.

Nevertheless, our model does not account for physical phenomenon in the electricity grids and their affect on the market speculation. While general consensus is that the shoulder months exhibit lower volatility and summer months exhibit higher volatility, it is important for the participants to know different cases (where the price and load swings differently from their forecasts) as it was shown in the example cases. Since the weather forecast has huge impact on load and price changes, the virtual trader probably speculates more often than hedging. The speculators do bring more liquidity to the market; however, as shown in Section 8.4.2.3, speculators can influence RT price by changing their bidding habits. The proposed model does not capture such market gaming except through the GARCH component that captures the realized volatility in the model.

The analysis presented in this dissertation provides some evidence that it is possible for a market participant with significant presence to manipulate the market price. While simulating this particular market gaming example, the profitability is tested by changing amounts of the must run units. The resulting case still yields the same expected situation. However, market manipulation is illegal and the independent market monitors (IMM) commissioned by the ISOs and regulatory commissions such as FERC constantly monitor the market happenings. If they find a consistent pattern in bidding strategy which may cause to price manipulation, the law takes its own course of action against such manipulators. The latest case is of Edison Electric Company which was fined $7 million by FERC in May 2008 for possible market manipulation and data manipulation. Every time there is a sudden spike in market price, the IMMs investigate the situation.

In general, the virtuals are found to give an opportunity to the market participants to effectively shift their exposure. However, the constraint would be the feasibility of accurate forecasting and the bid and offer price the trader may be willing to submit. Since the market structure does not allow the trader to see what other participants are bidding or offering for, they have to rely on their model and expected bidding and offering amounts. Also, it is not necessary for your bid or offer to clear completely and even if it clears, the clearing price may not be attractive for the trader's purpose. This leads us to believe that although the main purpose for virtuals is to hedge, it is almost a speculative trading position. Clearly, the market structure and characteristics of the electricity market does not allow the trader to perfectly hedge his or her position using virtual.

There are other examples where virtuals are used as a risk management tool against congestion risk. These strategies have not been discussed in this dissertation.

Researchers have indicated that the traders can also manipulate the market using the virtuals and financial products related to the congestions. The trader can use heavy volume of the virtuals to over schedule a particular CPNode area in DA market and then taking opposite position in the RT market using the virtuals. Such manipulation is obviously illegal.

While the proposed simulation models serve its main purpose of demonstrating virtual trading and how hedgers and speculators can manage their trades, they can further be improved. The following section discusses some of the drawbacks of the model and possible improvements.

i) It was assumed that the congestion cost will be reflected in the actual market observed price. While it is true, the market speculation can also spike the price up. Therefore, it may not reflect true congestion cost or energy cost. Therefore, breaking down the price into its original components—energy cost, congestion cost and loss component will probably help to improve the performance.

ii) MISO publishes the shadow price for different CPNodes. Shadow price reflects the possible congestion cost in different nodes. Inclusion of shadow price will probably improve the performance of our models.

iii) Transmission line and unit outages are major issues in electricity market which can rise price speculation, congestion cost etc. Therefore, including outage information into the statistical model will help explain the impact of sudden changes in the market dynamics.

iv) We had divided the weeks based on weekend and weekdays. However, people's energy usage pattern is different depending on different days. In fact, although Friday is a weekday, people's usage pattern change significantly from Thursday to Friday. So, the performance may improve by dividing the week into three parts—Monday through Thursday, Friday, Saturday and Sunday. Other possibility is modeling each day separately.

v) Weather is an important part of the electricity market. The model was built based on daily average of weather variables. The hourly weather could significantly vary within the day and that would affect the load and price information. Therefore, the model performance will significantly improve if actual hourly weather data is included.

vi) The price models could become more robust if gas and oil prices are included.

8.6. CONCLUSION

The MISO electricity market is relatively new in the US and the market structure is still improving. The electricity market dynamics change from market to market. The objective of this dissertation was to test the strategies under certain MISO market conditions. The proposed models were built and tested based on the MISO day-ahead and real time load data, Cinergy hub Locational Marginal Prices (LMP) and virtual bids and offers cleared at the same node. Since virtuals are relatively new financial products, it was important to test different hedging and speculative strategies involving virtuals. The motivation to analyze the virtuals came from the fact there are only a few literature that explicitly describe different hedging strategies involving the virtuals in this market. There are some market structure literatures that describe how virtuals may affect the market. This dissertation stands different from those. Instead of testing the market structure, a statistical simulation model is proposed to test how hedgers and speculators can use the available information to make an investment decision. The models test how different trading scenarios perform under different conditions. Based on the discussions presented in this dissertation, it can be concluded that the virtuals are helpful tools to manage the DA/RT risks. The key is to have an accurate understanding how the market moves. The simulation models serve the purpose.

The analysis presented in this thesis shows that the cleared virtual supply volume and the difference between cleared virtual supply and bids help in price divergence. However, regression coefficients for these two explanatory variables are small. This indicates that the rate at which virtuals alone may affect the price divergence is not very large. There are other explanatory variables that help understand the divergence that exists between DA and RT price. Also, the virtual bid appears to be safer strategy during the summer and winter periods and the virtual offer trading is more profitable during shoulder months. The model performance and robustness can improve if several other important variables are tested and possibly included.

APPENDIX A.
WEATHER DATA

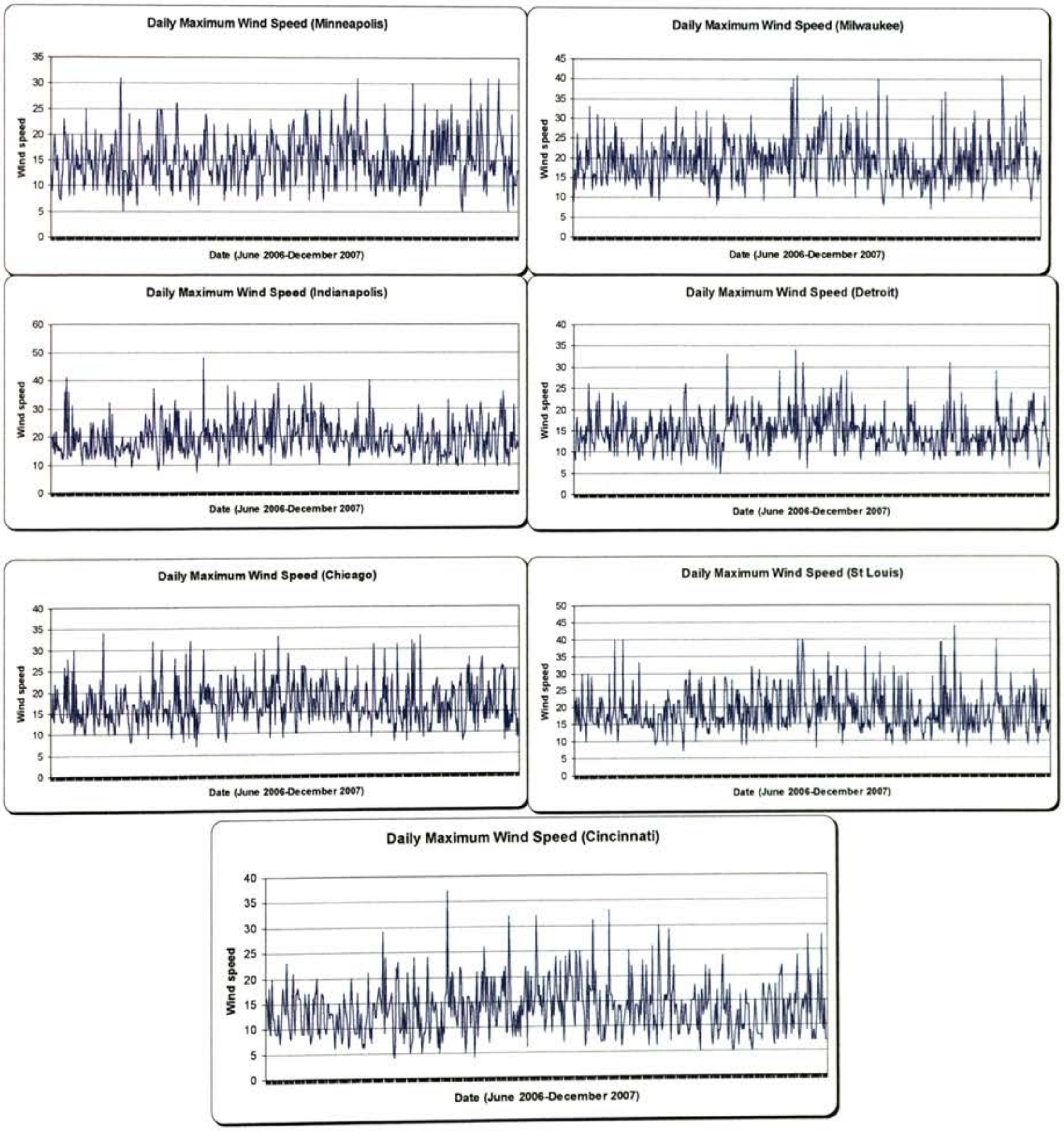

Figure A.1. Daily Maximum Wind Speed in Seven Cities across MISO Footprint

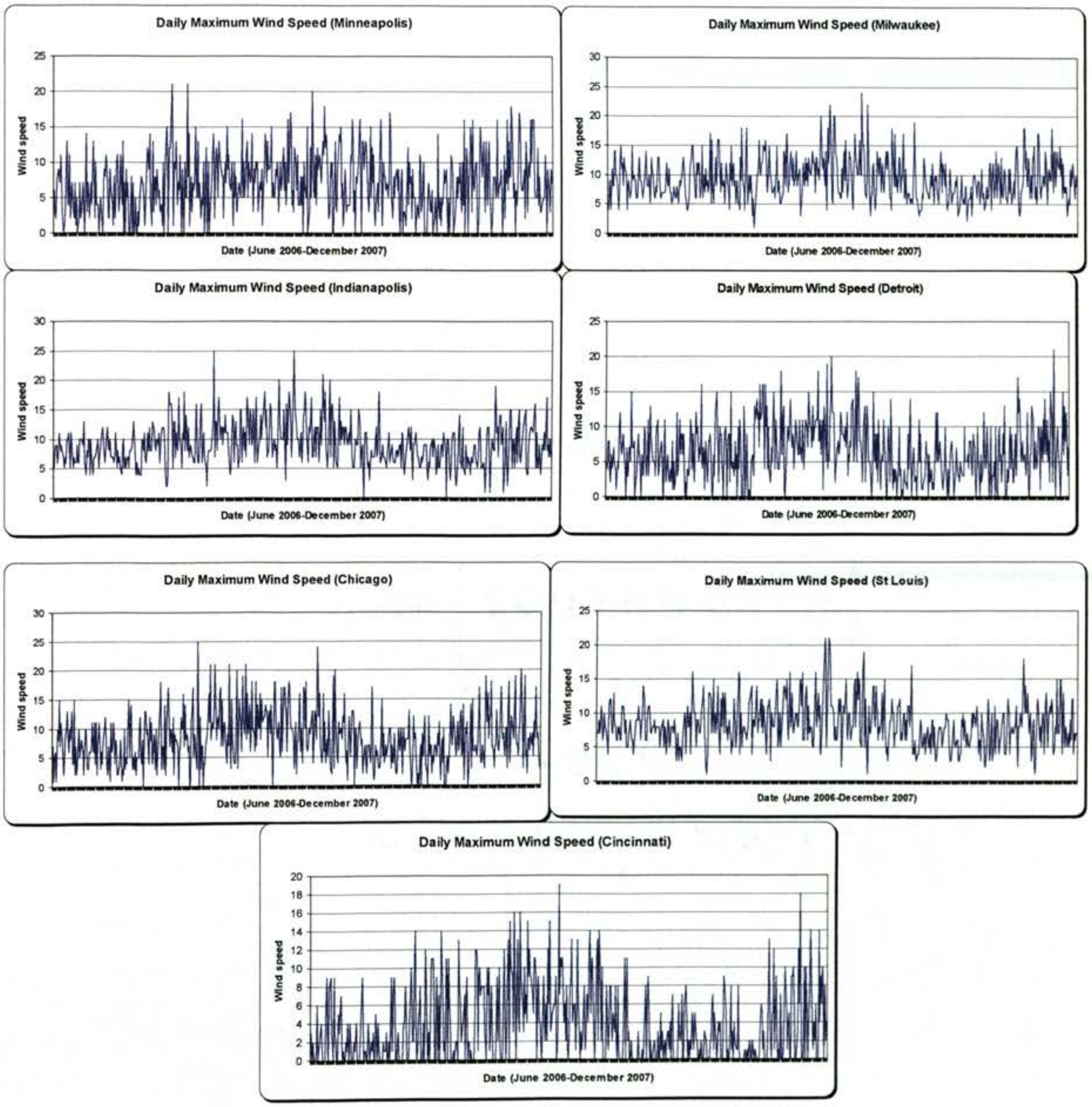

Figure A.2. Daily Mean Wind Speed in Seven Cities across MISO Footprint

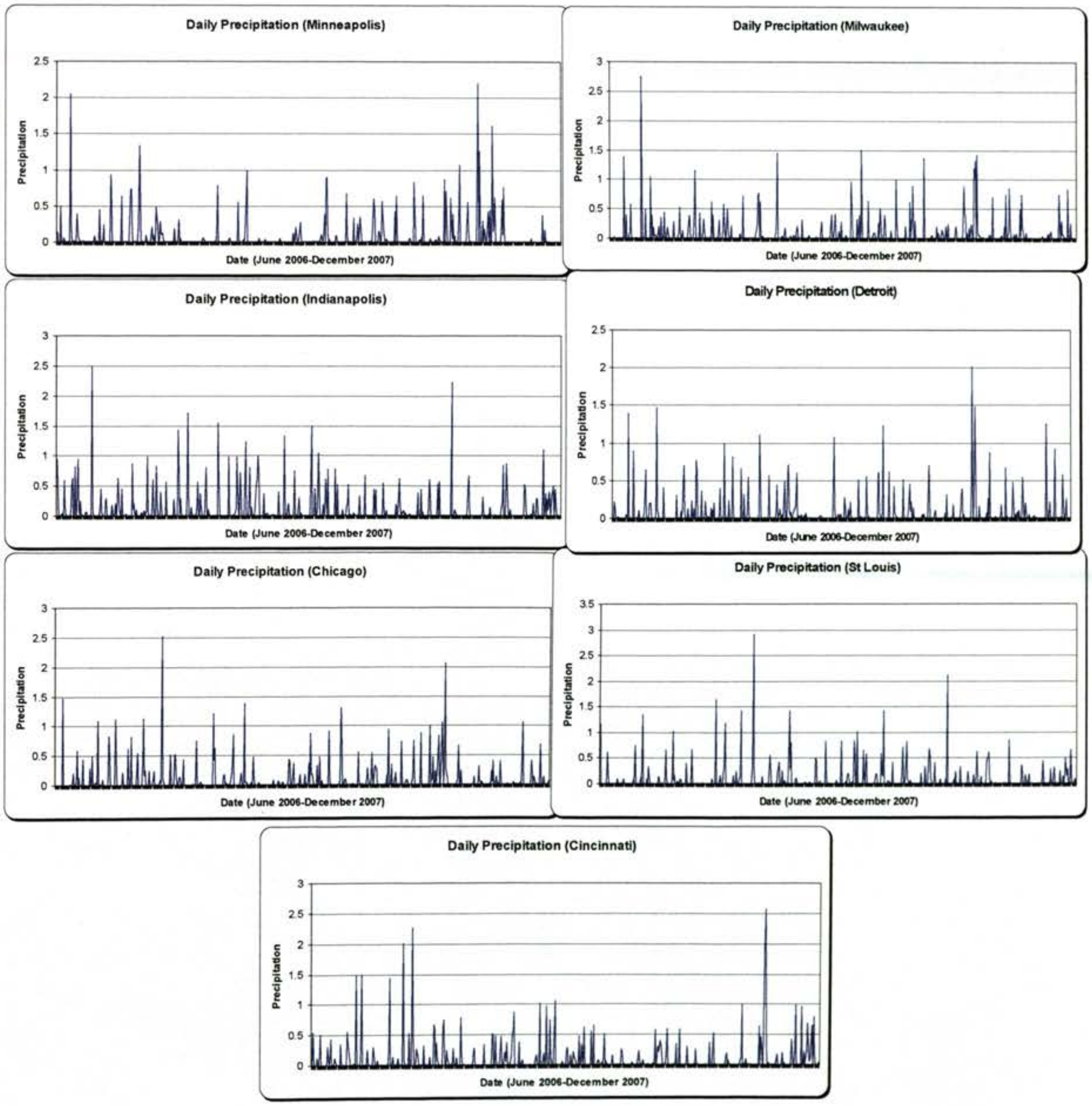

Figure A.3. Daily Precipitation in Seven Cities across MISO Footprint

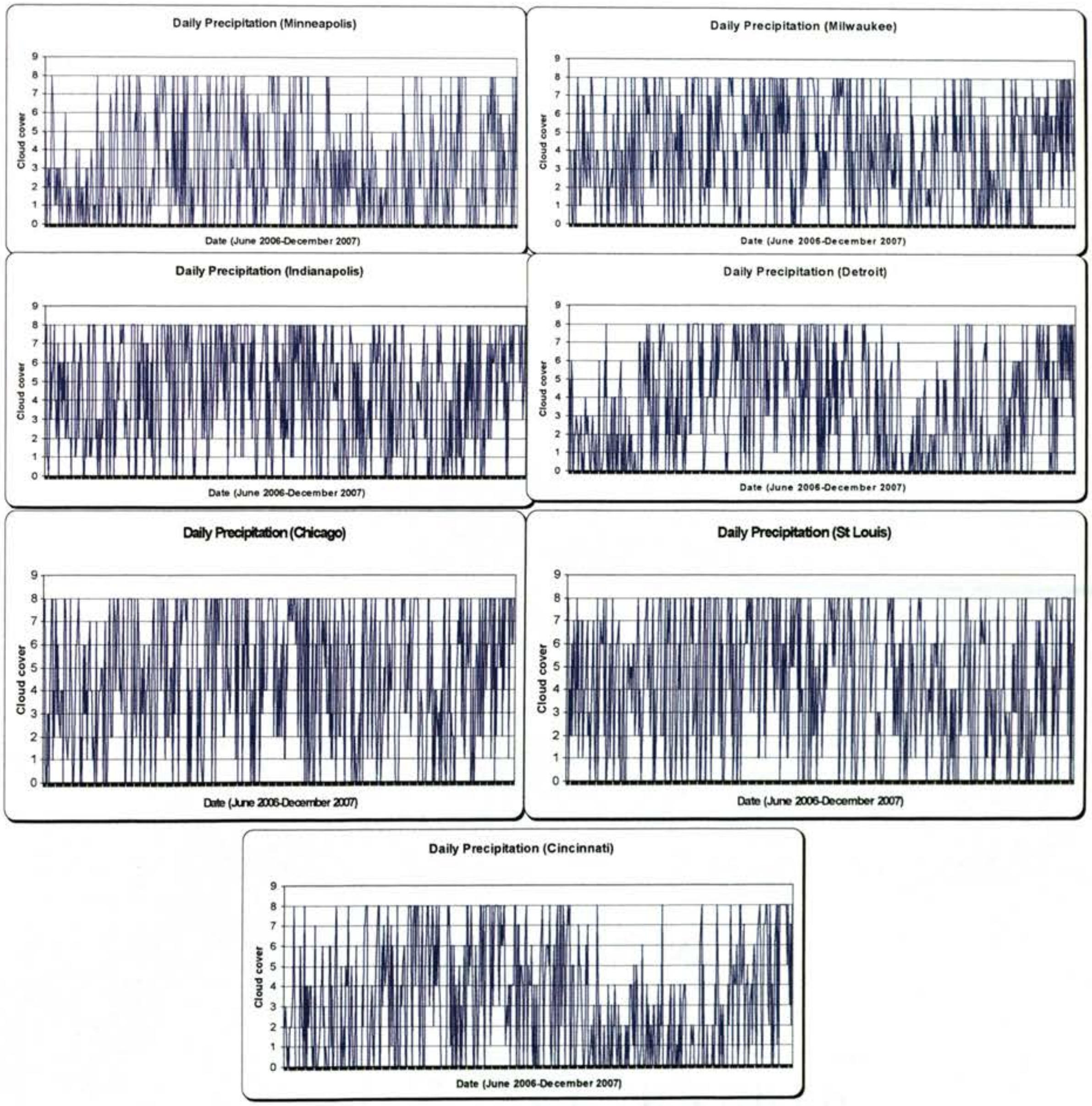

Figure A.3. Daily Cloud cover in Seven Cities across MISO Footprint

APPENDIX B.

PRINCIPAL COMPONENT ANALYSIS

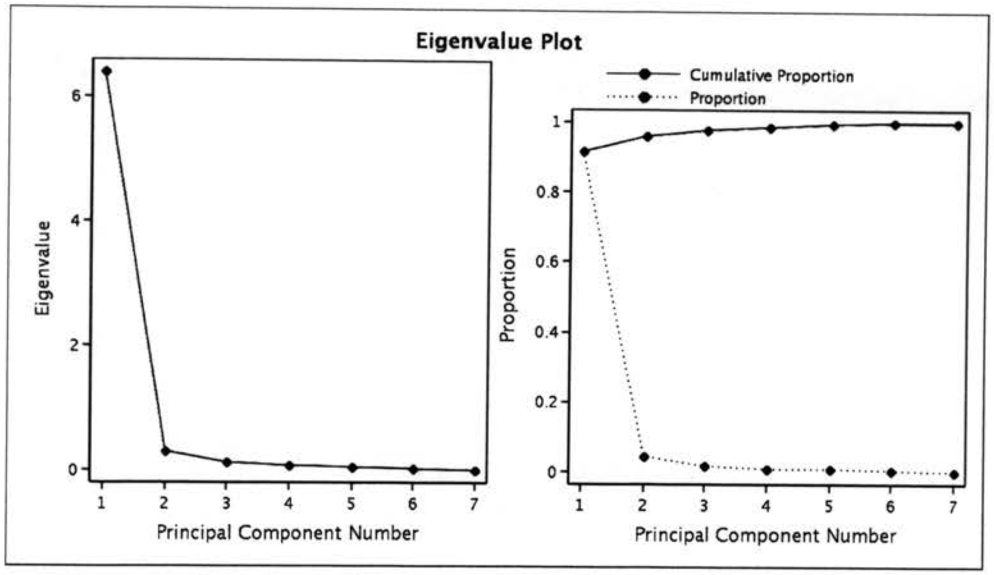

Figure B.1. PCA of CDD

Table B.1. Eigen Vectors of PCs of the CDD

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Detroit_CDD	0.381749	-.306007	-.061851	-.664336	0.104160	-.389385	0.391138
Minneapolis_CDD	0.374083	-.339738	0.690451	0.060115	-.161381	0.477940	0.099161
Cinci_CDD	0.379737	-.317306	-.537806	-.111082	0.131546	0.418558	-.510928
Stl_CDD	0.379547	-.338851	-.089680	0.696520	0.019636	-.496394	0.033900
Milwauki_CDD	0.380005	0.403637	0.210019	-.182225	-.459257	-.333748	-.541345
Chicago_CDD	0.372827	0.488537	0.181504	0.066824	0.763607	0.042740	-.000269
Indianapolis_CDD	0.377715	0.416945	-.380949	0.141045	-.389108	0.291787	0.530968

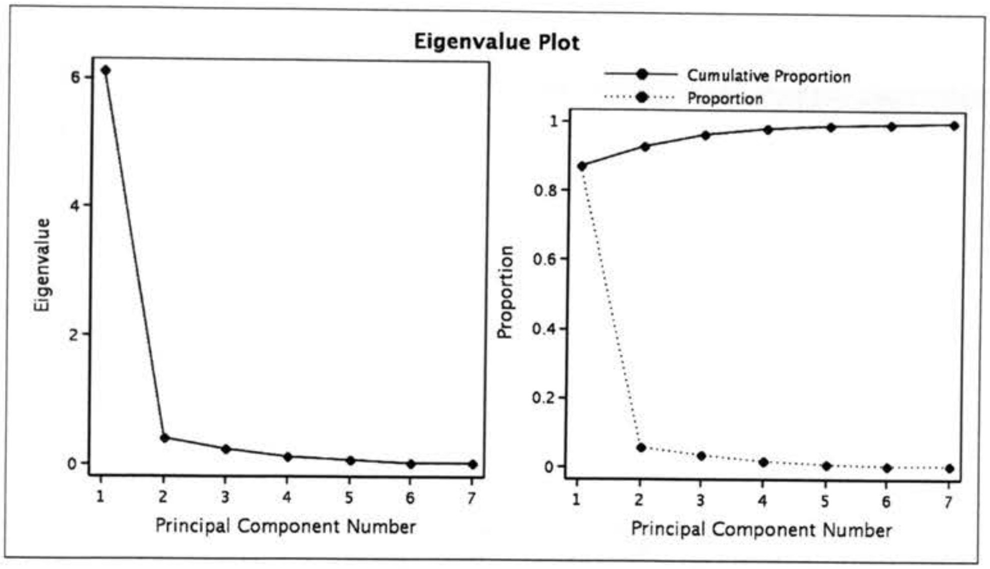

Figure B.2. PCA of HDD

Table B.2. Eigen Vectors of PCs of the HDD

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Detroit_HDD	0.382723	0.036148	-.411334	0.584145	-.580320	0.060308	0.037246
Minneapolis_HDD	0.349737	0.571526	0.676144	0.290232	0.084878	0.031970	0.037576
Cinci_HDD	0.377533	-.490136	0.050416	0.245297	0.460250	0.491252	-.318377
Stl_HDD	0.378157	-.311699	0.357735	-.543102	-.547373	0.183889	0.058934
Milwauki_HDD	0.374240	0.404864	-.446675	-.376994	0.271197	0.352686	0.395540
Chicago_HDD	0.393483	0.199002	-.205383	-.264733	0.059065	-.455865	-.694264
Indianapolis_HDD	0.388315	-.362140	0.037648	0.084864	0.259885	-.622894	0.503894

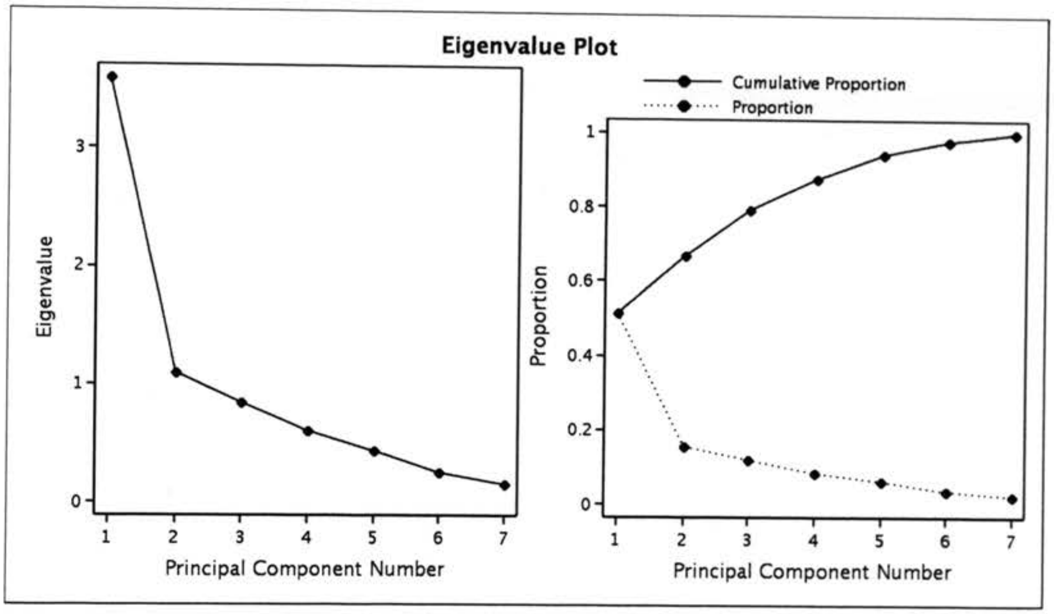

Figure B.3. PCA of Cloud Cover

Table B.3. Eigen Vectors of PCs of the Cloud Cover

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.233608	0.681393	0.171815	0.660853	-.062635	-.100652	0.028779
Milwaukee	0.417620	0.371273	-.017625	-.443366	-.115192	0.467870	-.508620
Indianapolis	0.449342	-.291785	-.131022	0.077734	-.195777	-.657648	-.467883
Detroit	0.364474	-.116551	0.567945	-.102200	0.715673	-.074943	0.052571
Chicago	0.449689	0.200060	-.198597	-.395074	-.170309	-.230821	0.692783
stl	0.333987	-.199847	-.669753	0.348433	0.408815	0.328761	0.057662
Cincinnati	0.350004	-.468160	0.377399	0.269671	-.485959	0.414111	0.188485

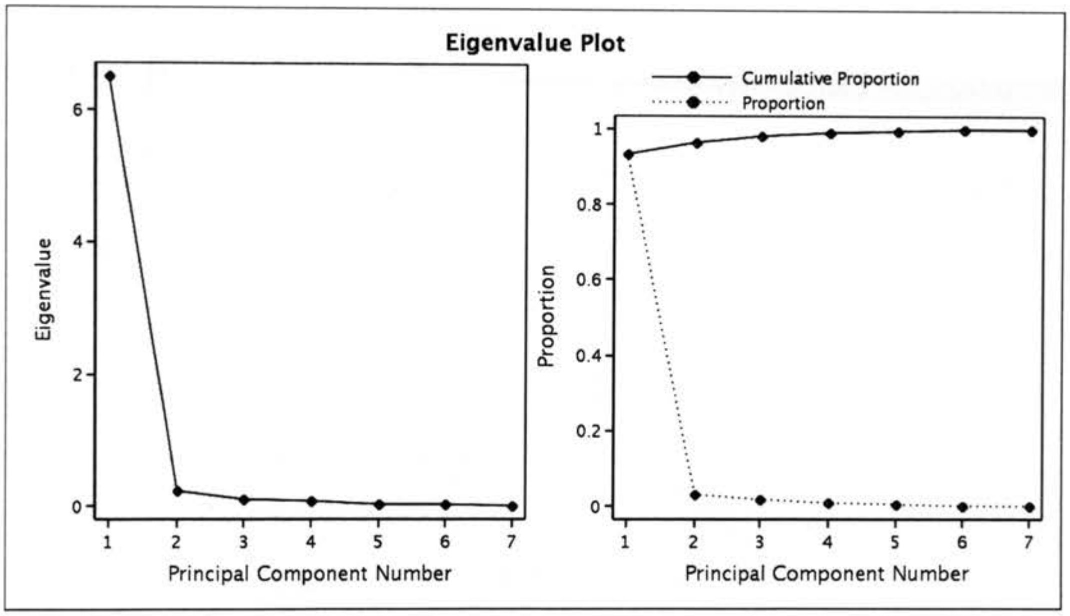

Figure B.4. PCA of Maximum Dew Point

Table B.4. Eigen Vectors of PCs of the Maximum Dew Point

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.361356	0.747748	0.119616	0.502809	0.066387	0.181854	0.075451
Milwaukee	0.383667	0.256188	-.245138	-.305372	-.336158	-.455110	-.560084
Indianapolis	0.381936	-.387122	0.110488	0.130707	-.193668	0.657433	-.453039
Detroit	0.378153	-.156468	-.649308	0.012916	0.637430	0.025026	0.061703
Chicago	0.385876	0.055984	-.117699	-.462997	-.396700	0.241730	0.635564
StLouis	0.377334	-.043050	0.682223	-.373792	0.475668	-.155316	-.015293
Cincinnati	0.376915	-.442615	0.111848	0.531595	-.234808	-.494372	0.259587

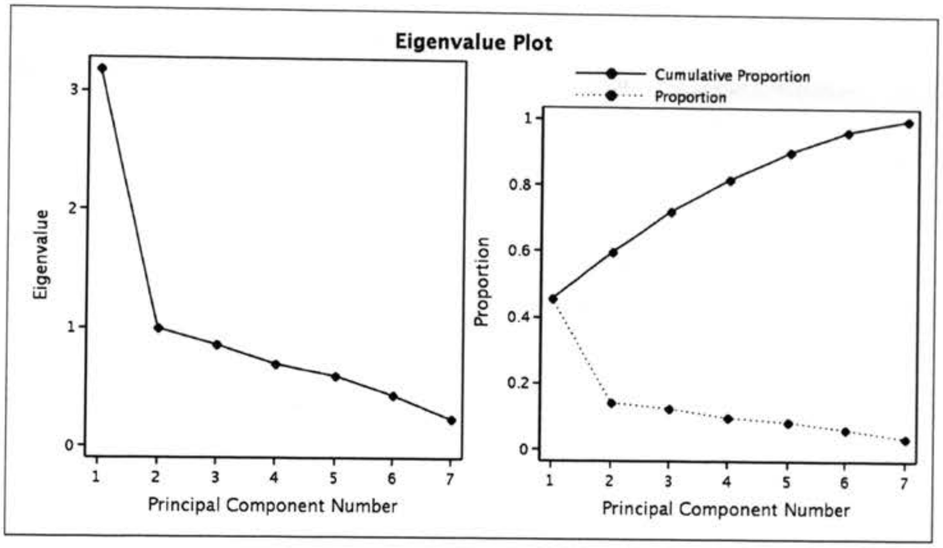

Figure B.5. PCA of Maximum Humidity

Table B.5. Eigen Vectors of PCs of the Maximum Humidity

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.249611	-.535859	0.670421	0.346552	0.280201	-.000015	0.049740
Milwaukee	0.430846	-.356635	-.064120	-.247639	-.497790	0.037242	-.610381
Indianapolis	0.409355	0.416632	-.043999	0.198310	0.355451	-.603148	-.357001
Detroit	0.385643	-.142783	-.368038	-.303264	0.634212	0.447765	0.027431
Chicago	0.466666	-.197274	-.239898	-.065865	-.259084	-.381596	0.684599
stl	0.372511	0.341401	-.088179	0.633629	-.262429	0.512674	0.060962
Cincinnati	0.281482	0.486031	0.586267	-.530525	-.095539	0.160878	0.156094

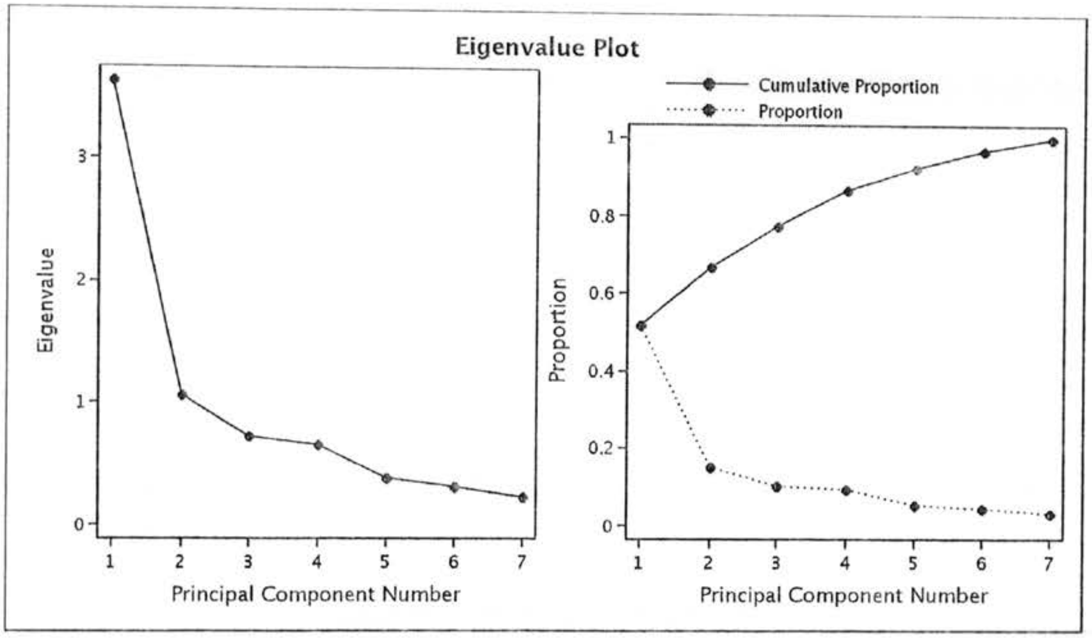

Figure B.6. PCA of Maximum Wind Speed

Table B.6. Eigen Vectors of PCs of the Maximum Wind Speed

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.194563	0.767484	0.184353	0.556854	-.067162	0.156389	0.008521
Milwaukee	0.392749	0.350316	-.352660	-.315913	-.075486	-.693666	-.109482
Indianapolis	0.440059	-.293085	0.193225	0.138588	-.281128	0.090246	-.759427
Detroit	0.395042	-.142424	-.486367	0.242226	0.693149	0.217436	-.026421
Chicago	0.425878	0.084614	-.222409	-.408529	-.408894	0.579625	0.303229
stl	0.351743	0.067592	0.705370	-.392536	0.454419	-.014255	0.115660
Cincinnati	0.391265	-.412717	0.144029	0.437324	-.237934	-.320591	0.552439

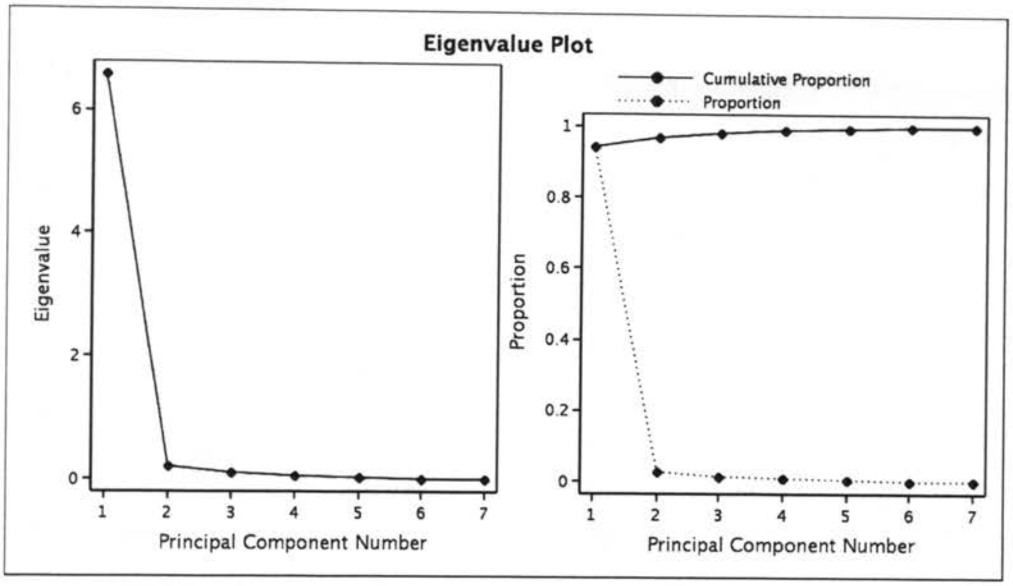

Figure B.7. PCA of Mean Dew Point

Table B.7. Eigen Vectors of PCs of the Mean Dew Point

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.364423	0.741756	0.125504	0.518437	-.010570	-.163812	0.074294
Milwaukee	0.382805	0.268933	-.201168	-.405712	-.282734	0.380693	-.592620
Indianapolis	0.381541	-.394306	0.098995	0.107003	-.166690	-.695957	-.406888
Detroit	0.376231	-.147089	-.687824	0.125296	0.585371	0.032481	0.065574
Chicago	0.385165	0.063253	-.101714	-.509649	-.303059	-.229626	0.658017
StLouis	0.377179	-.070066	0.662075	-.262265	0.564714	0.163683	0.002375
Cincinnati	0.378044	-.437550	0.110404	0.459290	-.372502	0.513134	0.201077

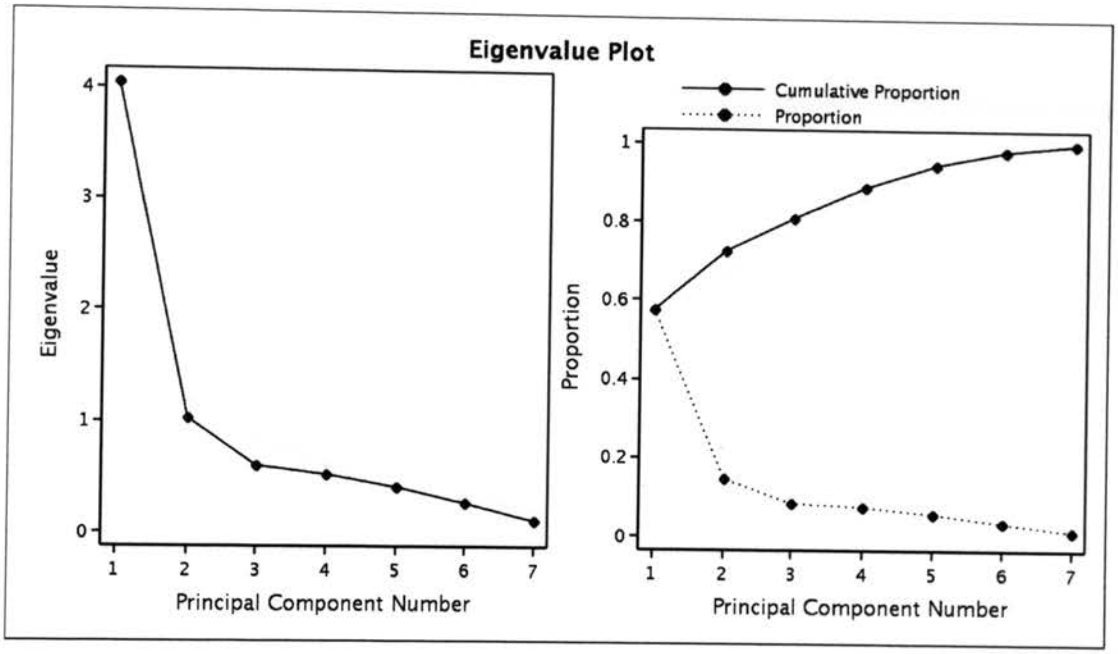

Figure B.8. PCA of Mean Humidity

Table B.8. Eigen Vectors of PCs of the Mean Humidity

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.271992	0.606890	0.645018	0.299670	0.215847	-.064399	0.033443
Milwaukee	0.387329	0.394633	-.143912	-.363283	-.524415	0.223659	-.465319
Indianapolis	0.424087	-.341963	-.029706	0.165199	0.204159	-.566355	-.559105
Detroit	0.388966	0.100051	-.523193	0.352066	0.445278	0.491767	0.030116
Chicago	0.441199	0.161835	-.284615	-.225531	-.089815	-.481022	0.638619
stl	0.352466	-.365618	0.386045	-.602225	0.346217	0.318047	0.096771
Cincinnati	0.354913	-.434895	0.242055	0.462000	-.557237	0.225168	0.227279

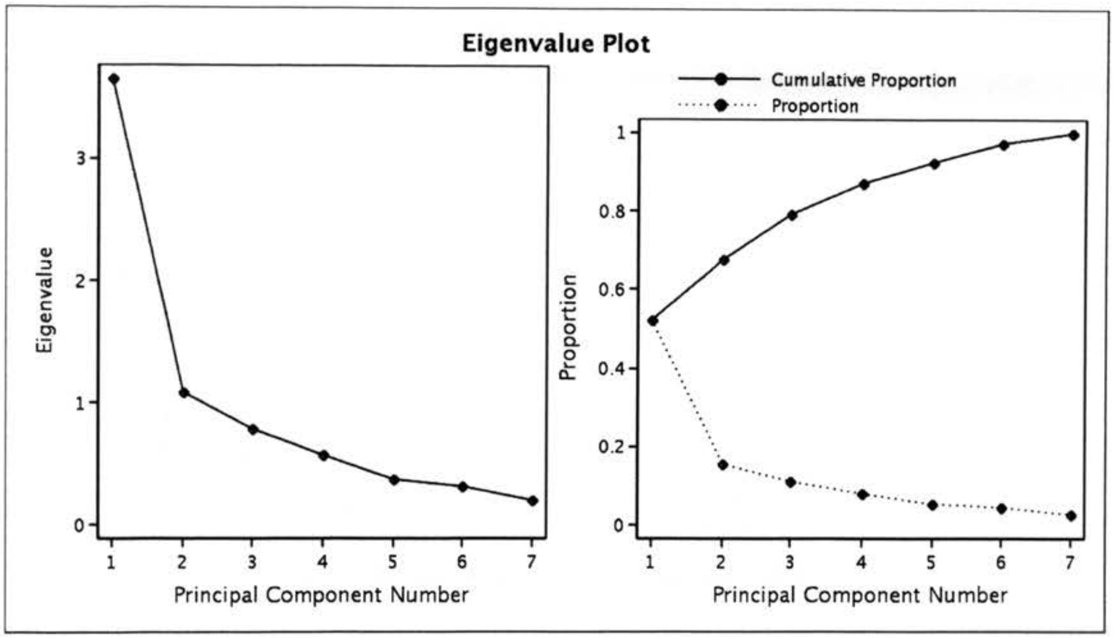

Figure B.9. PCA of Mean Wind Speed

Table B.9. Eigen Vectors of PCs of the Mean Wind Speed

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.259905	0.523911	0.672440	0.349964	0.198075	-.205683	-.042153
Milwaukee	0.396387	0.413979	-.026027	-.262902	-.326308	0.703212	0.026821
Indianapolis	0.454673	-.080904	-.316068	0.233752	0.005241	-.100456	-.788714
Detroit	0.366224	-.405000	0.270877	-.445647	0.633342	0.169496	-.005345
Chicago	0.428414	-.068569	0.088618	-.442624	-.480986	-.592599	0.159591
stl	0.384261	0.247943	-.573093	0.205089	0.371332	-.154193	0.508633
Cincinnati	0.321379	-.563375	0.193866	0.563195	-.289663	0.222302	0.302042

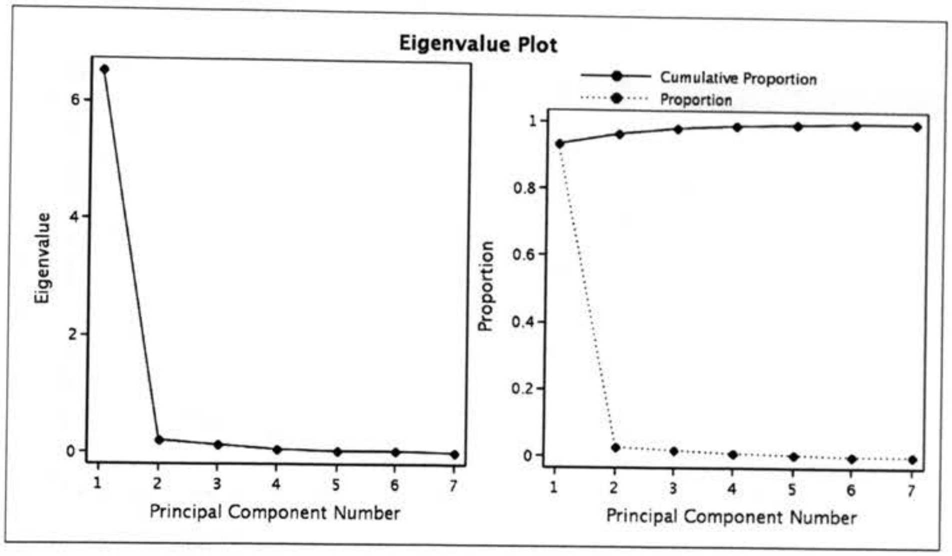

Figure B.10. PCA of Minimum Dew Point

Table B.10. Eigen Vectors of PCs of the Minimum Dew Point

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.365865	0.704393	0.276097	0.505599	-.089186	-.121518	0.124068
Milwaukee	0.383151	0.298028	-.205869	-.386705	-.183594	0.226276	-.698243
Indianapolis	0.382165	-.396688	0.028759	0.106188	-.148353	-.777759	-.239935
Detroit	0.375934	-.079119	-.650090	0.298380	0.567518	0.107445	0.084536
Chicago	0.384663	0.103299	-.201353	-.542533	-.264930	-.096253	0.653472
StLouis	0.375934	-.140184	0.631653	-.290778	0.582692	0.125994	0.008878
Cincinnati	0.377717	-.470178	0.135703	0.340041	-.452257	0.540778	0.072410

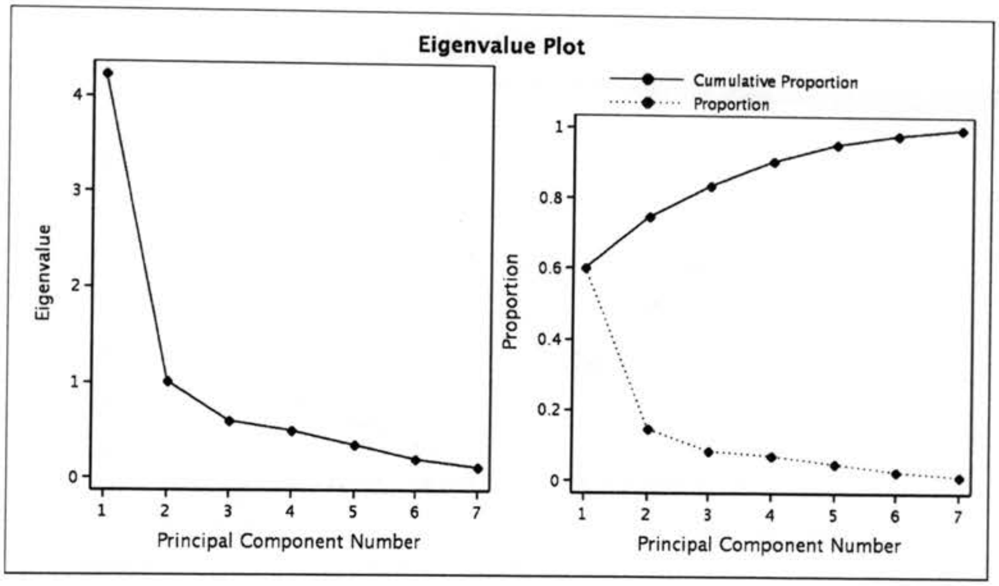

Figure B.11. PCA of Minimum Humidity

Table B.11. Eigen Vectors of PCs of the Minimum Humidity

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.263530	0.604806	0.734202	-.120097	-.077343	-.072776	0.002734
Milwaukee	0.371107	0.413938	-.390477	0.387874	-.256777	0.465110	-.325200
Indianapolis	0.428293	-.333273	0.040039	-.189666	-.114841	-.406086	-.699874
Detroit	0.392087	0.126976	-.235773	-.511270	0.678028	0.221989	0.064480
Chicago	0.430520	0.160759	-.342899	0.133609	-.146114	-.610470	0.509269
stl	0.350952	-.362645	0.333923	0.653004	0.433504	0.091502	0.105370
Cincinnati	0.383602	-.422275	0.148991	-.305768	-.495880	0.427955	0.360275

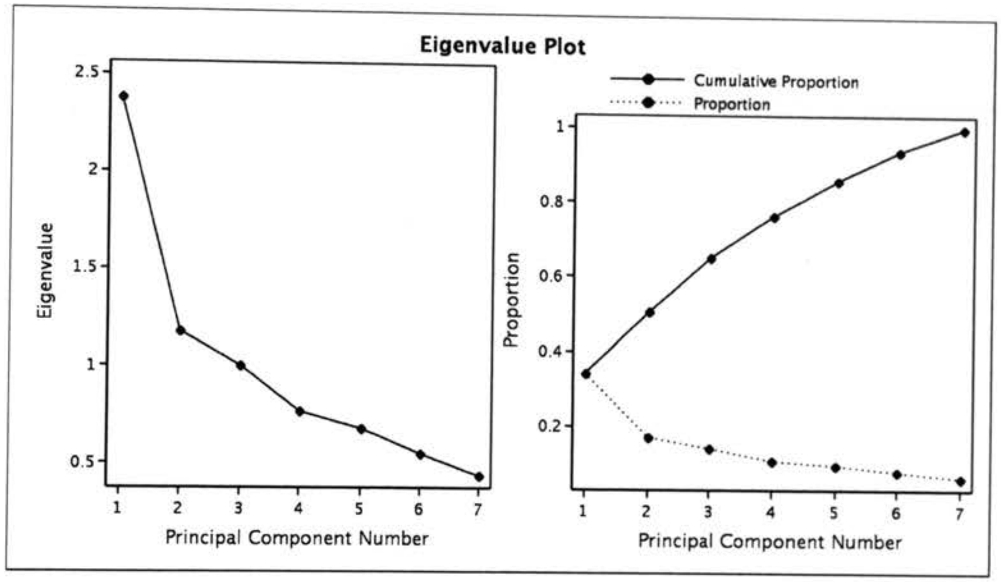

Figure B.12. PCA of Precipitation

Table B.12. Eigen Vectors of PCs of the Precipitation

Eigenvectors							
	Prin1	Prin2	Prin3	Prin4	Prin5	Prin6	Prin7
Minneapolis	0.027161	0.279100	0.927004	-.099670	0.226570	-.025596	0.010279
Milwaukee	0.333386	0.580715	-.070300	-.129405	-.464474	0.557128	0.061717
Indianapolis	0.505018	-.291258	0.079487	-.075995	-.016225	0.069066	-.801872
Detroit	0.439416	0.043548	-.222256	-.089789	0.782106	0.266600	0.254541
Chicago	0.374803	0.511992	-.156091	0.270753	0.004832	-.704983	-.051868
stl	0.362899	-.348477	0.220584	0.730890	-.193375	0.146534	0.324259
Cincinnati	0.409651	-.338488	0.083567	-.593275	-.289067	-.307625	0.424807

APPENDIX C.
COMPUTER PROGRAMS

C.1. SAS Program for DA Demand

```
ods rtf;
ods graphics on;
proc ucm data=dademanddata;
id HR interval=hour;
model DADemand_phy= Dum_Peak Dum_WKD tmpprnhdd tmphdd_tomo tmpprncdd
Seadum1 Seadum2 MinHumPrn1 MinHumPrn2 MinHumPrn3 MinHumPrn4 MaxWindPrn1
MaxWindPrn2 MaxWindPrn3 MaxWindPrn4 MaxWindPrn5 MeanWindPrn1
MeanWindPrn2 MeanWindPrn3 MeanWindPrn4 MeanWindPrn5 preciPrn1
preciPrn2 preciPrn3 preciPrn4 preciPrn5 preciPrn6 cloudPrn1 cloudPrn2
cloudPrn3 cloudPrn4 cloudPrn5
;
irregular;
cycle period=24 noest=period plot=smooth;
run;
ods graphics off;
ods _all_ close;
```

C.2. SAS Program for DA Price

```
ods rtf;
ods graphics on;
proc  autoreg data=dapdata;
model  LogDAprice = LogDAprice_t_1 LogDAprice_t_24  DADemand_phy
                    Seaduml Seadum2  Dum_Peak Dum_WKD
/garch=(p=1,q=1) noint;
run;
ods graphics off;
ods rtf close;
```

C.3. SAS Program for RT Price

```
ods rtf;
ods graphics on;
proc  autoreg data=allprice2;
model lnP_t = lnP_t_1 RTLoad Net_Schedu_Imports Gen_reso_Must_Run
Gen_Reso_Emerg Seadum1 Seadum2 Dum_Peak Dum_WKD
/ garch=(p=1,q=1) noint;
run;
ods graphics off;
ods rtf close;
```

C.4. Block Bootstrap

```
clear all;
clc;
[A,B,C]=xlsread('C:\pcadata4Jan_Final','pcresidualdata','b1:ab373');
minhum1=A(:,1);
minhum2=A(:,2);
minhum3=A(:,3);
minhum4=A(:,4);
maxwind1=A(:,5);
maxwind2=A(:,6);
maxwind3=A(:,7);
maxwind4=A(:,8);
meanwind1=A(:,10);
meanwind2=A(:,11);
meanwind3=A(:,12);
meanwind4=A(:,13);
meanwind5=A(:,14);
precip1=A(:,15);
precip2=A(:,16);
precip3=A(:,17);
precip4=A(:,18);
precip5=A(:,19);
cloud1=A(:,21);
cloud2=A(:,22);
cloud3=A(:,23);
temp1cdd=A(:,26);
temp1hdd=A(:,27);
n=372;
l=31;
k=12;
blks=unidrnd(k,1,k);
for i=1:k
new_minhum1(((i-1)*l+1):(i*l))=minhum1(((blks(i)-1)*l+1):(blks(i)*l));
new_minhum2(((i-1)*l+1):(i*l))=minhum2(((blks(i)-1)*l+1):(blks(i)*l));
new_minhum3(((i-1)*l+1):(i*l))=minhum3(((blks(i)-1)*l+1):(blks(i)*l));
new_minhum4(((i-1)*l+1):(i*l))=minhum4(((blks(i)-1)*l+1):(blks(i)*l));
new_maxwind1(((i-1)*l+1):(i*l))=maxwind1(((blks(i)-1)*l+1):(blks(i)*l));
new_maxwind2(((i-1)*l+1):(i*l))=maxwind2(((blks(i)-1)*l+1):(blks(i)*l));
new_maxwind3(((i-1)*l+1):(i*l))=maxwind3(((blks(i)-1)*l+1):(blks(i)*l));
new_maxwind4(((i-1)*l+1):(i*l))=maxwind4(((blks(i)-1)*l+1):(blks(i)*l));
new_meanwind1(((i-1)*l+1):(i*l))=meanwind1(((blks(i)-
1)*l+1):(blks(i)*l));
new_meanwind2(((i-1)*l+1):(i*l))=meanwind2(((blks(i)-
1)*l+1):(blks(i)*l));
new_meanwind3(((i-1)*l+1):(i*l))=meanwind3(((blks(i)-
1)*l+1):(blks(i)*l));
new_meanwind4(((i-1)*l+1):(i*l))=meanwind4(((blks(i)-
1)*l+1):(blks(i)*l));
new_meanwind5(((i-1)*l+1):(i*l))=meanwind5(((blks(i)-
1)*l+1):(blks(i)*l));
new_precip1(((i-1)*l+1):(i*l))=precip1(((blks(i)-1)*l+1):(blks(i)*l));
new_precip2(((i-1)*l+1):(i*l))=precip2(((blks(i)-1)*l+1):(blks(i)*l));
new_precip3(((i-1)*l+1):(i*l))=precip3(((blks(i)-1)*l+1):(blks(i)*l));
new_precip4(((i-1)*l+1):(i*l))=precip4(((blks(i)-1)*l+1):(blks(i)*l));
new_precip5(((i-1)*l+1):(i*l))=precip5(((blks(i)-1)*l+1):(blks(i)*l));
new_cloud1(((i-1)*l+1):(i*l))=cloud1(((blks(i)-1)*l+1):(blks(i)*l));
```

```
new_cloud2(((i-1)*l+1):(i*l))=cloud2(((blks(i)-1)*l+1):(blks(i)*l));
new_cloud3(((i-1)*l+1):(i*l))=cloud3(((blks(i)-1)*l+1):(blks(i)*l));
new_temp1cdd(((i-1)*l+1):(i*l))=temp1cdd(((blks(i)-1)*l+1):(blks(i)*l));
new_temp1hdd(((i-1)*l+1):(i*l))=temp1hdd(((blks(i)-1)*l+1):(blks(i)*l));
end

blcboot_minhum1=new_minhum1';
blcboot_minhum2=new_minhum2';
blcboot_minhum3=new_minhum3';
blcboot_minhum4=new_minhum4';
blcboot_maxwind1=new_maxwind1';
blcboot_maxwind2=new_maxwind2';
blcboot_maxwind3=new_maxwind3';
blcboot_maxwind4=new_maxwind4';
blcboot_maxwind4=new_maxwind4';
blcboot_maxwind4=new_maxwind4';
blcboot_maxwind4=new_maxwind4';
blcboot_maxwind4=new_maxwind4';
blcboot_meanwind1=new_meanwind1';
blcboot_meanwind2=new_meanwind2';
blcboot_meanwind3=new_meanwind3';
blcboot_meanwind4=new_meanwind4';
blcboot_meanwind5=new_meanwind5';
blcboot_precip1=new_precip1';
blcboot_precip2=new_precip2';
blcboot_precip3=new_precip3';
blcboot_precip4=new_precip4';
blcboot_precip5=new_precip5';
blcboot_cloud1=new_cloud1';
blcboot_cloud2=new_cloud2';
blcboot_cloud3=new_cloud3';
blcboot_temp1cdd=new_temp1cdd';
blcboot_temp1hdd=new_temp1hdd';

for m=1:31
    blockboot_minhum11(m,:)=blcboot_minhum1(m,:);
    blockboot_minhum12(m,:)=blcboot_minhum2(m,:);
    blockboot_minhum13(m,:)=blcboot_minhum3(m,:);
    blockboot_minhum14(m,:)=blcboot_minhum4(m,:);
    blockboot_maxwind1(m,:)=blcboot_maxwind1(m,:);
    blockboot_maxwind2(m,:)=blcboot_maxwind2(m,:);
    blockboot_maxwind3(m,:)=blcboot_maxwind3(m,:);
    blockboot_maxwind4(m,:)=blcboot_maxwind4(m,:);
    blockboot_meanwind1(m,:)=blcboot_meanwind1(m,:);
    blockboot_meanwind2(m,:)=blcboot_meanwind2(m,:);
    blockboot_meanwind3(m,:)=blcboot_meanwind3(m,:);
    blockboot_meanwind4(m,:)=blcboot_meanwind4(m,:);
    blockboot_meanwind5(m,:)=blcboot_meanwind5(m,:);
    blockboot_precip1(m,:)=blcboot_precip1(m,:);
    blockboot_precip2(m,:)=blcboot_precip2(m,:);
    blockboot_precip3(m,:)=blcboot_precip3(m,:);
    blockboot_precip4(m,:)=blcboot_precip4(m,:);
    blockboot_precip5(m,:)=blcboot_precip5(m,:);

    blockboot_cloud1(m,:)=blcboot_cloud1(m,:);
    blockboot_cloud2(m,:)=blcboot_cloud2(m,:);
    blockboot_cloud3(m,:)=blcboot_cloud3(m,:);
```

```
    blockboot_cdd(m,:)=blcboot_temp1cdd(m,:);
    blockboot_hdd(m,:)=blcboot_temp1hdd(m,:);
    m=m+1;
 end

bootstrppc_allvariable=[blockboot_minhum11, blockboot_minhum12,
blockboot_minhum13,  blockboot_minhum14, blockboot_maxwind1,
blockboot_maxwind2, blockboot_maxwind3, blockboot_maxwind4,
blockboot_meanwind1, blockboot_meanwind2, blockboot_meanwind3,
blockboot_meanwind4, blockboot_meanwind5, blockboot_precip1,
blockboot_precip2, blockboot_precip3, blockboot_precip4,
blockboot_precip5,blockboot_cloud1, blockboot_cloud2, blockboot_cloud3,
blockboot_cdd, blockboot_hdd] ;

[status, message]=xlswrite('C:\simoutput', bootstrppc_allvariable,
'simout');
```

C.4. Simulating DA Demand Process

```
clear all;
clc;

for col=1:1000

period=24;
lamda=(2*3.14)/period;
m=60.19;
he1=48.53;
mean=50.93;
m_mean=m-mean;
he1_mean=he1-mean;
beta=he1_mean;
alpha=sqrt((m_mean)^2 - (he1_mean)^2);
damping_factor=.96714;
rho= damping_factor;
sigma_v=sqrt(.0493748);
A=[cos(lamda) sin(lamda); -sin(lamda) cos(lamda)];

for t=2:745
    v(t,:)=normrnd(0,sigma_v);
    v_star(t,:)=normrnd(0,sigma_v);
    psi(1,1)=alpha;
    psi_star(1,1)=beta;
    psi(t,:)= psi(t-1)*cos(lamda)*rho+ psi_star(t- 1)*sin(lamda)
*rho+v(t,:);
    psi_star(t,:)=-psi(t-1)*sin(lamda)*rho+ cos(lamda)*psi_star(t-1)
*rho+v_star(t,:);
    t=1+1;
end
psi_final=psi;

irreg=.0000001059335;
[A,B,C]=xlsread('C:\PCA_2007HOURLY3','pc','d1:ae8761');
dum_pk=A(:,1);
dum_wkd=A(:,2);
seadum1=A(:,3);
seadum2=A(:,4);
minhum1=A(:,5);
minhum2=A(:,6);
minhum3=A(:,7);
minhum4=A(:,8);
maxwind1=A(:,9);
maxwind2=A(:,10);
maxwind3=A(:,11);
maxwind4=A(:,12);
meanwind1=A(:,13);
meanwind2=A(:,14);
meanwind3=A(:,15);
meanwind4=A(:,16);
meanwind5=A(:,17);
precip1=A(:,18);
precip2=A(:,19);
precip3=A(:,20);
```

```
precip4=A(:,21);
precip5=A(:,22);
cloud1=A(:,23);
cloud2=A(:,24);
cloud3=A(:,25);
temp1cdd=A(:,26);
temp1hdd=A(:,27);
temphddtom=A(:,28);

for h=2:745
dad(h,:)=irreg+.96714*psi_final(h,:)+3.24391*dum_pk(h,:)+4.75425*dum_wkd
(h,:)+.27157*temp1hdd(h,:)+.09662*temp1cdd(h,:)+.23298*minhum1(h,:)+.048
99*minhum2(h,:)+.0721*minhum3(h,:)+.02834*minhum4(h,:)+.63719*maxwind1(h
,:)+.27705*maxwind2(h,:)-.08672*maxwind3(h,:)+0.09610*maxwind4(h,:)-
0.37646*meanwind1(h,:)-.18672*meanwind2(h,:)+.21156*meanwind3(h,:)-
.18099*meanwind4(h,:)+.19371*meanwind5(h,:)-6.77317*precip1(h,:)-
2.11522*precip2(h,:)-2.44678*precip3(h,:)+2.33523*precip4(h,:)-
1.71043*precip5(h,:)-.27438*cloud1(h,:)-.43525*cloud2(h,:)-
.21062*cloud3(h,:)+3.87488*seadum1(h,:)-
3.26998*seadum1(h,:)+.34917*temphddtom(h,:);
h=h+1;
end
dad_sim(:, col)=dad;
col=col+1;
end;

for avg=2:745
dad_fin2(avg,1)=MEAN(dad_sim(avg, 1:1000));
avg=avg+1;
end

dad_fin=dad_fin2;
[status, message]=xlswrite('C:\dad_simout', dad_fin, 'JanDAD_output');
```

C.5. DA Price process

```
clear all;
clc;
for col=1:1000
[A,B]=xlsread('C:\ DAPsimvar2007','dap');
a1=.3634;
a2=.5087;
a3=.006539;
a4=.007028;
a5=.0613;
a6=-0.0361;
a7=-.007017;
arch0=0.006295;
arch1=.7982;
garch1=0.0382;
h=zeros(8761,1);
e=zeros(8761,1);
epsilon=zeros(8761,1);
P=A(:,6);
dum_pk=A(:,1);
dum_wkd=A(:,2);
seadum1=A(:,3);
seadum2=A(:,4);
ld_fcst=A(:,5);
h0=randn(1);
e0=randn(1);
h(1,1)=h0;
e(1,1)=e0;

for i=2:745
    e(i,1)=randn(1);
    h(i)=arch0 + arch1*e(i-1,1)*e(i-1,1)+garch1*h(i-1,1);
    epsilon(i,1)=sqrt(h(i,1))*e(i,1);
    i=i+1;
end

ep=epsilon(:,1);

for t=25:770
    P(t,:)=a1*P(t-1,1)+a2*P(t-24,1)+a3*ld_fcst(t,:)+a4*dum_pk(t,:)+
a5*dum_wkd(t,:)+a6*seadum1(t,:)+a7*seadum2(t,:)+ ep(t,:);
    t=t+1;
end
P(:, col)=P;
col=col+1;
end;

for avg=2:745
dap_fin2(avg,1)=MEAN(P(avg, 1:1000));
avg=avg+1;
end

dap_fin=dap_fin2;
P_n=exp(dap_fin (:,1));
[status, message]=xlswrite('C:\dap_sim', P_n, 'DAprc_simuout');
```

C.6. Simulating RT Load Process

```
clear all;
clc;

for col=1:1000

period=24;
lamda=(2*3.14)/period;
m=60.19;
he1=48.53;
mean=50.93;
m_mean=m-mean;
he1_mean=he1-mean;
beta=he1_mean;
alpha=sqrt((m_mean)^2 - (he1_mean)^2);
damping_factor=.87442;
rho= damping_factor;
sigma_v=sqrt(1.88735);
A=[cos(lamda) sin(lamda); -sin(lamda) cos(lamda)];

for t=2:745
    v(t,:)=normrnd(0,sigma_v);
    v_star(t,:)=normrnd(0,sigma_v);
    psi(1,1)=alpha;
    psi_star(1,1)=beta;
    psi(t,:)= psi(t-1)*cos(lamda)*rho+ psi_star(t-1)*sin(lamda) *
rho+v(t,:);
    psi_star(t,:)=-psi(t-1)*sin(lamda)*rho+ cos(lamda)*psi_star(t-1) *
rho+v_star(t,:);
    t=1+1;
end

psi_final=psi;
irreg=.000000122741;
[A,B,C]=xlsread('C:\RTLoadsim','2007','a1:q8761');
dum_pk=A(:,1);
dum_wkd=A(:,2);
seadum1=A(:,3);
seadum2=A(:,4);
minhum1=A(:,5);
minhum2=A(:,6);
minhum3=A(:,7);
maxwind1=A(:,8);
maxwind2=A(:,9);
meanwind1=A(:,10);
precip1=A(:,11);
precip2=A(:,12);
cloud1=A(:,13);
cloud2=A(:,14);
cloud3=A(:,15);
temp1cdd=A(:,16);
temp1hdd=A(:,17);
```

```
for h=2:745
    rtl(1,:)=58.049;
    rtl(h,:)=irreg+.87442*psi_final(h,:)+.84847*rtl(h-
1,:)+1.28357*dum_pk(h,:)+.53386*dum_wkd(h,:)+.60800*seaduml(h,:)-
0.63207*seadum2(h,:)+0.09347*templhdd(h,:)+.01704*templcdd(h,:)+.04013*m
inhuml(h,:)+.00614*minhum2(h,:)+.01334*minhum3(h,:)+.08731*maxwindl(h,:)
+.04618*maxwind2(h,:)-.04290*meanwindl(h,:)-1.20852*precipl(h,:)-
.33181*precip2(h,:)-.06358*cloudl(h,:)-.07139*cloud2(h,:)-
.02395*cloud3(h,:);
    h=h+1;
end

rtl_sim(:, col)=rtl;
col=col+1;
end;

for avg=2:745
rtl_fin2(avg,1)=MEAN(rtl_sim(avg, 1:1000));
avg=avg+1;
end

rtl_fin=dad_fin2;
rtload_final=rtl_fin;
[status, message]=xlswrite('C:\rtl_simout', rtload_final,'rtl_simnout');
```

C.7. Simulating RT Price Process

```
clear all;
clc;

for col=1:1000

[A,B]=xlsread('C:\dummy_sim','2007-2');
dum_pk=A(:,3);
dum_wkd=A(:,4);
seadum1=A(:,5);
seadum2=A(:,6);
ld_fcst=A(:,7);
scdimp=A(:,8);
mstrun=A(:,9);
emgncy=A(:,10);
h=zeros(8762,1);
e=zeros(8762,1);
epsilon=zeros(8762,1);
lnP=zeros(8762,1);
h0=randn(1);
e0=randn(1);
h(1,1)=h0;
e(1,1)=e0;

for i=2:745
    e(i,1)=randn(1);
    h(i)=0.0703 + 0.1662*e(i-1,1)*e(i-1,1)+0.333*h(i-1,1);
    epsilon(i,1)=sqrt(h(i,1))*e(i,1);
    i=i+1;
end

ep=epsilon(:,1);
lnP(1,1)=2.897016;

for t=2:745
    lnP(t,:)=.6043*lnP(t-1,1)+0.0180*ld_fcst(t,:)+0.0918*dum_pk(t,:)-
0.0426*dum_wkd(t,:)-.1398*seadum1(t,:)-0.0534*seadum2(t,:)+
ep(t,:)+0.005440*mstrun(t,:)+0.0190*emgncy(t,:)-0.0262*scdimp(t,:);
    t=t+1;
end
P(:, col)=lnP;
col=col+1;
end;

for avg=2:745
rtp_fin2(avg,1)=MEAN(P(avg, 1:1000));
avg=avg+1;
end

rtp_fin=rtp_fin2;
RTP_n=exp(rtp_fin(:,1));
[status, message]=xlswrite('C:\ rtp_sim', RTP_n, 'RTP_simuout');
```

BIBLIOGRAPHY

Bartels R., and Fiebig D., "Residential End-use Electricity Demand: Results from A Designed Experiment," The Energy Journal, Vol. 21, pp 51-81, 2000.

Bollerslev T., "Generalized Autoregressive Conditional Heteroskedasticity," Journal of Econometrics, Vol. 31, pp 307-327, 1986.

Brennan M. J., "The Price of Convenience and Valuation of Commodity Contingent Claims," Lund D, and Oksendal B, Stochastic Models and Option Models, 1st ed., North Holland Publisher, 1991.

Chow T. W. S., and Leung C.T., "Neural Network based Short-Term Load Forecasting Using Weather Compensation," IEEE Transactions on Power Systems, Vol. 11, No. 4, , pp 1736-1742, November 1996

Cuaresmaa J. C., Hlouskovab J., Kossmeierc S., and Obersteinerd M., "Forecasting Electricity Spot-prices Using Linear Univariate Time-series Models," Applied Energy, Vol. 77, pp 87–106, 2004.

de Jong C. and Huisman R., "Option Formulas for Power Prices with Spikes, Energy & Power Risk Management," ERIM Report Series Reference No. ERS-2002-96-F&A, pp 12-16, 2003.

De Vany A. S. & Walls D. W., "Price Dynamics in a Network of Decentralized Power Markets," Journal of Regulatory Economics, Springer, Vol. 15(2), pp 123-40, March, 1999.

De Vany A. S. & Walls D. W., "Cointegration Analysis of Spot Electricity Prices: Insights on Transmission Efficiency in the Western US," Energy Economics, Elsevier, vol. 21(5), pages 435-448, October, 1999.

Diebold F. X., and Mariano R. S., "Comparing Predictive Accuracy," Journal of Business and Economic Statistics, Vol. 13, pp. 253–63, 1995.

Dong Z. Y., Li X., Xu Z., and Teo K. L., "Weather Dependent Electricity Market Forecasting with Neural Networks, Wavelet and Data Mining Techniques," Proceedings from 2003 Australasian Universities Power Engineering Conference (AUPEC 2003), 2003.

Douglas A. P., Breipohl A. M., Lee F. N., and Adapa R., "The Impacts of Temperature Forecast Uncertainty on Bayesian Load Forecasting," Power Systems, IEEE Transactions, Vol. 13, pp 1507-1513, 1998.

Duffie D., Gray S., and Hoang P., Volatility in Energy Prices, Chapter in Managing Energy Price Risk, 2nd ed. Risk Books, 1999.

Engle R. F., and Granger C. W. J., "Co-integration and Error Correction: Representation, Estimation and Testing," Econometrica, Vol. 35, pp 251- 276, 1987

Engle R. F., Mustafa C., and Rice J., "Modeling Peak Electricity Demand," Journal of Forecasting, Vol. 11, pp. 241-251, 1992.

Fushuan W. and. Kumar D. A., "Optimal Bidding Strategies and Modeling of Imperfect Information Among Competitive Generators," IEEE Transaction on Power Systems, 16-1, 2001.

Escribano A., Pena J.I., and Villaplana P., "Modeling Electricity Prices: International Evidence," Working Paper 02-27, Economics Series 02, Universidad Carlos III de Madrid 2002.

Eydeland A., and Wolyniec K., Energy and Power Risk Management: New Development in Modeling, Pricing and Hedging, 1rt ed. John Wiley & Sons, Inc, 2003.

Fernandez-Morales A., "Decomposing Seasonal Concentration," Annals of Tourism Research, Vol. 30, No. 4, pp. 942–956, 2003.

Gibson R., and Schwartz E., "Stochastic Convenience Yield and the Pricing of Oil Contingent Claim," Journal of Finance, Vol. 45, No. 3, pp 959–976, July 1990.

Gross G. and Finlay D. J., "Optimal Bidding Strategies in Competitive Electricity Markets," in proceedings of 12th Power Systems Computation Conference (PSCC'96), pp. 815–823, Dresden, 1996.

Greene W., "Econometric Analysis," 4th International Edition, Prentice-Hall, New Jersey, 2000.

Guthrie G., and Videbeck S., "High-frequency Electricity Spot Price Dynamics: An Intraday Markets Approach," Research Paper, New Zealand Institute for the Study of Competition and Regulation, 2002.

Hadsell L., and Shawky H., "Electricity Price Volatility and the Marginal Cost of Congestion: An Empirical Study of Peak Hours on the NYISO Market, 2001-2004," The Energy Journal, Vol. 27, No. 2, pp 157-179, 2006.

Harris C., Electricity Markets: Pricing, Structures and Economics, 1st ed. John Wiley & Sons, Inc, 2006.

Harvey A.C, "Trends and Cycles in Macroeconomic Time Series," Journal of Business and Economic Statistics, Vol. 3, pp 216–227, 1985.

Harvey A.C, Forecasting, Structural Time-series Models and the Kalman Filter, 1st ed. Cambridge University Press, Cambridge, 1989.

Harvey A.C, "Testing in Unobserved Components Models," Journal of Forecasting, Vol. 20, pp 1-19, 2001

Harvey A.C., and Jaeger A., "Detrending, Stylized Facts and the Business Cycle," Journal of Applied Econometrics, Vol. 8, pp 231–47, 1993.

Harvey A.C., and Koopman S., "Forecasting Hourly Electricity Demand Using Time-Varying Splines," Journal of the American Statistical Association, Vol. 88, pp 1228-1253, 1993.

Irismi G., Widergren S. and Yehsakul P., "On-line Load Forecasting for Energy Control Center Application," IEEE Trans Power Apparatus and Systems, Vol. 101, No 1, pp 71-78, Jan 1982.

Isemonger A. G. and Rahimi F. A., "Design Criteria for Convergence Bidding," CAISO Stakeholder Meeting, Folsom, 2006.

Isabel M., and Soares R.T., "The European Power Industry: Asymmetries and Price Volatility," Proceeding of Energy and Power Systems, 2005.

Jarrow R., and Rudd A., "Approximate Option Valuation for Arbitrary Stochastic Processes," Journal of Financial Economics, Vol. 10, pp 347-369, 1982

Kalman R. E., "A New Approach to Linear Filtering and Prediction Problems," Journal of Basic Engineering, Transactions ASME, Series D 82, pp 35-45, 1960.

Knittel C.R., and Roberts M., "An Empirical Examination of Deregulated Electricity Prices," POWER, Working Paper, PWP-087.

Lamont J. W., and Rajan S., "Strategic Bidding in an Energy Brokerage," IEEE Transaction on Power Systems, Vol. 12, No 4, pp 1729–1733, 1997.

Lapson E., and Hunter R., "Credit Risk in Liberalised Power and Natural Gas Market," chapter in Managing Energy Price Risk, 2nd ed. Risk Books, 1999.

London J., "Modeling Derivatives Applications in Matlab, C++, and Excel," 1st ed., FT Press, New Jersey, 2007.

Mirasgedisa S., Sarafidisa Y., Georgopouloua E., Lalasa D.P., Moschovitsb M., Karagiannisb F., and Papakonstantinoub D., "Models for Mid-term Electricity Demand Forecasting Incorporating Weather Influences," Energy, Vol. 31, pp 208–227, 2006

Mount T., "Strategic Behavior in Spot Markets for Electricity when Load is Stochastic," Proceedings of the 33rd International Hawaii Conference on System Sciences, 2000.

Nagarajan S., "Power Forward Curves: A Managerial; Perspective," Chapter in Managing Energy Price Risk, 2nd ed., Risk Books, 1999.

Owayedh M. S., Al-Bassam A. A., and Khan Z. R., "Identification of Temperature and Social Events Effects on Weekly Demand Behavior," Proceedings of the Power Engineering Society Summer Meeting, Vol. 4, pp 2397-2402, 2000.

Palacio D.R., and Edenor S.A., "Simple Model for Load Forecast Weather Sensitive," CIRED 2001, Conference Publication No. 482, IEEE 2001.

Peng T. M., Hubele N. F. and Karady G. G., "An Adaptive Neural Network Approach to One-Week Ahead Load Forecasting," IEEE Trans. Power Systems, Vol. 8, No 3, pp 1195-1203, Aug. 1993.

Sewalt M., and De Jong C., "Negative Prices in Electricity Markets," Commodities Now, pp 74-77, 2003.

SAS Institute Inc., SAS/ETS User's Guide, Version 9, Cary, NC, SAS Institute Inc., 2002.

Shawky H.A., Marathe A., Barrett C. L., "A First Look at the Empirical Relationship between Spot and Futures Electricity Prices in the United States," The Journal of Futures Markets, Vol. 23, No 10, pp 931–955, 2003.

Skantze, P. L., and Ilic, M.D., Valuation, Hedging, and Speculation in Competitive Electricity Market: A Fundamental Approach, 1st ed. Kluwer Academic Publishing Group, 2001.

Smith M., "Modeling and Short-Term Forecasting of New South Wales Electricity System Load," in Journal of Business and Economic Statistics, Vol. 18, pp 465-478, 2000.

Taylor J. W., and Buizza R., "Neural Network Load Forecasting With Weather Ensemble Predictions," IEEE Transactions on Power Systems, Vol. 17, No. 3, 2002.

von der Fehr N. M., and Harbord D., "Spot Market Competition in the UK Electricity Industry," Economic Journal, Vol. 103, No 418, pp 531-546, 1993.

Walls, W. D., "Competition, Prices, and Efficiency in the Deregulated Gas Pipeline Network: A Multivariate Cointegration Analysis," Journal of Energy and Development, Vol. 36, No. 6, pp 416-416, November 1995.

Walls W. D., "Natural Gas and Electricity Markets," Forthcoming in L. Hunt and J. Evans, International Handbook on the Economics of Energy, Edward Elgar, 2008.

http://csdl2.computer.org/comp/proceedings/hicss/2000/0493/04/04934024.pdf. Alvarado F. L., "Understanding Price Volatility in Electricity Markets," 33rd Hawaii International Conference on System Sciences – 2000 (June 14, 2008).

http://www.lse.ac.uk/collections/cats/papersPDFs/65_EnsWFs&UtilitiesRisk_2004.pdf. Altalo M. G and Smith L. A., "Using ensemble weather forecasts to manage utilities risk," Environmental Finance, October 2004. (June 20, 2008).

http://www.tinbergen.nl/discussionpapers/03071.pdf. Carnero M. A., Koopman S. J., Ooms M., "Periodic Heteroskedastic RegARFIMA Models for Daily Electricity Spot Prices," (June 14, 2008).

http://ieeexplore.ieee.org/iel5/10834/34152/01627232.pdf?tp=&isnumber=&arnumber=1627232. Hua Z., Li X., Li-zi Z., "Electricity Price Forecasting Based on GARCH Model in Deregulated Market," (June 14, 2008).

http://uaelp.pennnet.com/display_article/321228/34/ARTCL/none/none/1/Energy-Credit-Risk-Management/. Inoussa R., "Energy Credit Risk Management, Electric Light & Power," (June 14, 2008).

http://web.gsm.uci.edu/~ashwang/papers/JOF_LongstaffWang.pdf . Longstaff F.A. and Wang A. W., "Electricity Forward Prices: A High-Frequency Empirical Analysis," (June 14, 2008).

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