VOLATILITY AND FORECASTING IN THE INDIAN SHORT TERM ELECTRICITY MARKET

by Sonal Gupta

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A thesis submitted to the

University of Petroleum and Energy Studies

For the Award of

Doctor of Philosophy

in

Power Management

BY

Sonal Gupta

June 2019

GUIDE

Dr. Deepankar Chakrabarti

Dr. Hiranmoy Roy

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Department of Power Management

School of Business

University of Petroleum and Energy Studies

Dehradun-248007, Uttarakhand

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Internal Supervisor
Dr. Deepankar Chakrabarti
Professor
Department of General Management
University of Petroleum and Energy Studies

Internal Co-Supervisor
Dr. Hiranmoy Roy
Associate Professor & Head of Department
Department of Economics and International Business
University of Petroleum and Energy Studies

Department of Power Management
School of Business
University of Petroleum and Energy Studies
Dehradun-248007: Uttarakhand

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June 2019

DECLARATION

I declare that the thesis entitled Volatility and Forecasting in the Indian Short term Electricity Market has been prepared by me under the guidance of Dr Deepankar Chakrabarti, Professor of Department of General Management, University of Petroleum and Energy Studies and Dr Hiranmoy Roy, Associate Professor of Department of Economics and International Business, University of Petroleum and Energy Studies. No part of this thesis has formed the basis for the award of any degree or fellowship previously.

Sonal.

Sonal Gupta

Department of Energy Management,
University of Petroleum and Energy Studies
"Knowledge Acres", Kandoli
Dehradun – 248 007
Uttarakhand

DATE : June 18, 2019

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CERTIFICATE

I certify that Ms. Sonal Gupta has prepared her thesis entitled **"Volatility and Forecasting in the Indian Short term Electricity Market"** for the award of PhD degree of the University of Petroleum & Energy Studies, under our guidance. She has carried out the work at the Department of Power Management, University of Petroleum & Energy Studies.

DChakrabarti

Internal Guide
Dr. Deepankar Chakrabarti
Professor, Department of General Management
University of Petroleum and Energy Studies
"Knowledge Acres", Kandoli
Dehradun – 248 007, Uttarakhand

17/6/19

Internal Co-guide
Dr. Hiranmoy Roy (Co- supervisor)
Associate Professor & Head of Department
Department of Economics and International Business
University of Petroleum and Energy Studies
"Knowledge Acres", Kandoli
Dehradun – 248 007, Uttarakhand

DATE: June 18, 2019

ABSTRACT

A robust trading system is vital to promote competition in the Indian Electricity Market. Globally, the electricity market is well developed (Srivastava, Kamalasadan, Patel, Sankar and Khalid, 2011; Bandyopadhayay, Roy and Ghosh, 2013). They have adopted numerous tools to mitigate risk risen due to extreme periods of spurts in the electricity markets making power trading a competitive and transparent process. Among the mature electricity markets across the globe such as Australia (NEMMCO- The National Electricity Market Management Company Limited), USA (PJM- Pennsylvania New Jersey Maryland Interconnection LLC), New Zealand (NZEM- New Zealand's electricity market) and Europe (Nordpool) the European electricity market design is simpler and open to introduce new products, with a low level of system integration and simplified transmission pricing rules. This makes the European market model, an "easy to adopt" market model for the developing markets.

The enactment of Electricity Act, 2003 (The Electricity Act, 2003 which has come into force from 10th June, 2003 repeals the Indian Electricity Act, 1910; Electricity (Supply) Act, 1948; and Electricity Regulatory Commissions Act, 1998) has bought a revolution in the Indian Electricity market. Earlier the electricity sector had a vertically integrated private or public monopoly market structure, which has been transformed into a competitive, efficient, liquid and transparent wholesale and retail mechanism (Mediratta et al, 2008). This had led to an increase in the number of private players and a change in the electricity pricing pattern.

The most unique factor which differentiates electricity from other commodities is that it is intangible and fungible. Therefore, various measures must be taken to either provide storage or to manage it properly. The storage cost of electricity is generally very high, hence an introduction to price modeling and pricing of derivatives is a better option.

In India, the electricity demand is seasonal, weather sensitive with variation in demand during different hours of the day. Also, there is a high demand-supply gap in the electricity market at geographical level i.e. energy deficit (Northern, Western and Southern) in certain regions and power surplus in other regions (Eastern and North Western) due to difference in the climatic conditions and loads in each region. Hence the need for power trading is inevitable. The Act defines Power Trading as "Purchase of electricity for resale thereof" and is now considered as separate and completely distinct activity with licensing from the Central Electricity Regulatory Commission (CERC) of India.

The Indian electricity market follows a voluntary decentralized market model, constituting of the following:

(i) Bilateral markets, i.e. long-term (ranging from 12 years to 25 years), medium-term and short-term markets (ranges between 15 minutes to 3 years);
(ii) Collective market, i.e., Indian Energy Exchange (IEX) constituting of day-ahead and term ahead segment
(iii) Real-time multilateral balancing market, i.e., Deviation Settlement Mechanism (DSM) (Sinha and Mathur, 2016).

Compared with countries in Europe, where volumes traded on short-term markets range from 23 percent to as much as 88 percent as of 2015, short-term power markets in India's account for about 10.48 percent of total power consumption in India (only 3.63 percent traded over exchanges, with bilateral contracts and deviation settlement mechanism/UI accounting for five percent and two percent respectively) (Central Electricity Regulatory Commission, 2008 – 2017; Sinha and Jain, 2017b). Whereas, the total volume traded on the Nord Pool Spot in 2015 was 489 TWh, more than 80% of the total Nordic/Baltic consumption. Hence, adoption of hedging techniques is required (Chaubey, 2016). Over a period of time, it has been observed that the power generation and distribution companies are shifting from Long-term contracts to Short-term or medium-term contracts (7-8 years) (Kujur, 2017).

There are various advantages of entering into Short Term contract over Long-term contracts, which are as follows (Jog, 2016; Dewan, 2016; Sinha and Jain, 2017a):

a) Short-term contracts offer lower prices of electricity compared to Long-term power purchase agreements. For that, I have conducted a price analysis of companies trading through long-term contracts and Indian Energy Exchange for the year 2016-17.
b) Immediate requirement is easily fulfilled by short-term contracts due to the presence of various product.
c) The price analysis is easier in short-term contracts using forecasting and volatility econometric tools compared to long-term contracts.

However, the short-term contracts are exposed to three kinds of major risks such as market risk, counterparty credit risk and liquidity risk amongst which trading through the exchange is only exposed to market/price/volatility risk. This risk needs to be addressed so that the traders can devise optimal profit maximization strategies.

The comparison states that trading through IEX is a better option than a long-term contract. If DisComs across the country replaced a quantum of the expensive power bought from PPAs with power from the exchange, they could have saved approximately INR 3200 crores in FY17 (Sinha and Jain, 2017b). Also if we study the case of three distribution companies viz. Uttarakhand Power Corporation Limited (UPCL), Assam Power Distribution Company Limited (APDCL) and West Bengal State Electricity Distribution Company Limited (WBSEDC), It has been observed that over a period of time with a shift from Long-term power purchase agreements to short-term agreements, there have been a decrease in the AT&C (Aggregate Technical & Commercial) losses in the respective companies. Hence, Indian DisComs needs to move towards a balanced mix of long-term and short-term contracts with the base load to be met by Long term and the energy surplus by the Short-term to reduce their losses. This also indicates prospects of power trading through exchanges especially for Open Access consumers and IPPs.

Indian Energy Exchange (IEX) is one of the leading power exchanges in India, which covers all the five regions (Northern, Southern, Western, Eastern and North- Eastern) of Indian electricity market offering anonymous and automatic bidding, enabling efficient price-discovery mechanism, risk management strategies and endeavouring to address the supply-demand gap.

IEX has further divided all the five regions mentioned above into 13 bid areas (Table 1: Annexure) to invite more participants (captive power plants, industrial consumers owning captive power plants, industrial consumers, independent power producers, state utilities and private distribution licensees) from each area to trade in the exchange.

The unique characteristics of electricity have led to rapid movements in the prices of the electricity traded in the Indian Energy Exchange's Day-Ahead Market (DAM) ranging from a low of -43.5 % in September 2009 to a high of 78% in March 2010 (authors own analysis).

The study of volatility in the electricity market dates back since the 1990s. Robert and Mount, (1998) stated various characteristics of electricity, which qualitatively differentiate it with other commodities. Electricity as a commodity cannot be stored, with inelastic demand, restrictive transportation networks (Girish and Vijaylakshmi, 2013), kinked supply curve and seasonal dependency being the major characteristics, differentiating it from other commodities.

All these features make electricity a volatile commodity and its forecasting a tedious task in comparison with other commodities. Despite gold and silver being riskier products, they are lesser volatile than electricity (Kirithiga, Naresh and Thiyagarajan, 2018)

Electricity prices generally exhibit seasonality at the annual, monthly, weekly, daily and intra-day level not only in India but across the globe (Girish and Vijayalakshmi, 2013). Especially if we observe the IEX prices of each region, i.e. Northern, Southern, Eastern, Western and North Eastern, each region has displayed uniqueness in its volatility patterns. The seasonal behavior is shown collectively, but if we delve deeper into each region, a completely different picture comes out. (author's own analysis: data collected from IEX site) (Indian Energy Exchange, 2017) Despite trading through the exchange is a better option for trading due to a lesser number of risks it is exposed to, still the existence of high volatility clustering has led to a huge financial impact on the stakeholders.

A random comparative price analysis (bid area wise) of IEX with short-term bilateral contracts was conducted during May 2017 (May being one of the most volatile months of the year due to the summer season. The data of bilateral contract was taken from Form IV of power trading companies with Chandigarh, Delhi, Punjab, Chhattisgarh, Maharashtra, Tamil Nadu & Kerala, and Karnataka & Telangana being the delivery point for N1, N2, N3, W3, W2, S2, and S1 respectively. It has been observed that due to high volatility, the stakeholders incurred huge losses ranging from as low as Rs. 0.02/kWh in N2 to as high as Rs. 0.49/kWh.

Factors such as temperature, water reservoir levels, fluctuations in the prices of fuels and changes in the regulations have tremendous effect on electricity DAM prices. In a power market, for both long-term and short-term contracts, study of volatility and price forecasting plays an important role which is an essential input for power market participants to devise effective bidding and risk mitigation strategies thereby leading to maximization of profits in the future. If the Independent power producers (IPP) or a Generator can adopt an appropriate method to forecast spot electricity prices accurately, then he will be in a better position to manage his own production schedule by taking a long or a short position, whichever is more profitable in the power exchange. DAM operates 24 X 7 consisting of 96 15-minute blocks in a day.

The process of research gap identification follows a funnel down approach in which I have first studied the Global Electricity Market, then the Indian Electricity Market to identify the area of research. Further, the determinants of the electricity prices were studied, where it was found that volatility in the electricity market is a huge problem and very few studies have been conducted in the India's Day ahead market to measure the intensity of volatility and to predict it, especially catering to each of the bid areas. Hence the need of this study arises.

In this thesis we have firstly studied volatility of the DAM's daily prices of all the 13 bid areas from August, 2008 to August, 2017. A comparative study of the two well-known volatility models i.e. GARCH (Generalized Autoregressive Conditional heteroskedasticity) and EGARCH (Exponential- Generalized Autoregressive Conditional heteroskedasticity) which have been sparsely applied in the Indian electricity market, has been applied. Further, an accurate forecasting technique among ARIMA (Autoregressive integrated moving average) and ANN (Artificial Neural Network) has been suggested which can be applied by the power market participants.

The results suggest that GARCH is a better volatility model when applied in all the bid areas of DAM and ANN has shown lesser value of error in comparison to ARIMA model while forecasting electricity prices.

With over 4400 Open Access Consumers in Indian electricity market, this study will help the power market stakeholders to understand the working of the Indian Day ahead market and will help them in effective bidding and adopting strategies to meet their short term and long-term requirements. The distribution companies will be able to plan their power purchase cost helping them in preparation of ARR (Annual Revenue Requirement). Also, the study will help the policy makers take an erudite decision to introduce risk management strategies i.e. electricity derivatives in the Indian power market, which has been successfully adopted in the sophisticated global electricity market.

The future scope of the study includes:

a) This research focuses only on the study of the Indian Electricity exchange market.
b) Impact of Renewable energy certificate trading on Spot electricity prices in India could be investigated in future
c) The objective of every power market participant is to hedge against extreme price movements (i.e. spikes or jumps) leading us to modelling and forecasting electricity spikes/jumps as one of the directions for future research

d) One of the most pronounced features of electricity prices is the Volatility it exhibits leading to consider Multivariate modelling and forecasting of electricity price volatility along with incorporating the impact of prices of one region on another

e) Modelling Indian spot electricity prices by considering exogenous variables such as electricity load, temperature, water reservoir levels, prices of fuels etc

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LIST OF SYMBOLS

Upper Case	Lower Case	In English
Α	α	Alpha
Β	β	Beta
Γ	γ	Gama
Δ	δ	Delta
Ε	Є, ε	Epsilon
Ζ	ζ	Zeta
Η	η	Eta
Θ	Θ, ϑ	Theta
Ι	ι	Iota
Κ	κ	Kappa
Λ	λ	Lambda
Μ	μ	Mu
Ν	ν	Nu
Ξ	ξ	Csi
Ο	ο	Omicron
Π	Π, ϖ	Pi
Ρ	Ρ, ϱ	Rho
Σ	Σ, ς	Sigma
Τ	τ	Tau
Υ	υ	Upsilon
Φ	Φ, φ	Phi
Χ	χ	Psi
Ψ	ψ	Chi
Ω	Ω	Omega

LIST OF ABBREVIATIONS

APDCL- Assam Power Distribution Company Limited

APARCH - Asymmetric Power Autoregressive Conditional Heteroskedasticity

ARFIMA- Autoregressive Fractionally Integrated Moving Average

ARR- Annual Revenue Requirement

BEE- Bureau of energy efficiency

BU- Billion units (1 unit=1kWh)

CRISIL- Credit Rating Information Services of India Limited

CERC-Central Electricity Regulatory Commission

CTU- Central Transmission Utility

DAC- Day-ahead contingency

DAM- Day-ahead market

DEKF-UD- Decoupled extended Kalman filter- U and D factorization

DCs- Designated consumers

DISCOMs- Distribution companies

DS- Designated sectors

EPF- Electricity price forecasting

ERCA- Electricity Regulatory Commission Act

ESA- Electricity supply act

ESCs- Energy saving certificates

FY- Financial year

GoI- Government of India

IEA- Indian Electricity Act

IEX- Indian Energy Exchange

IPPs- Independent power producers

LM- Lagrange Multiplier

MCMC- Markov Chain Monte Carlo

MCP- Market clearing price

MCV- Market clearing volume

NLDC- National load dispatch Centre

OA- Open access

PPA- Power purchase agreement

PXIL- Power exchange India limited

PXs- Power Exchange

RECs- Renewable energy certificates

RESs- Renewable energy sources

RLDC- Regional load dispatch centre

RPO- Renewable purchase obligation

SEBs- State electricity boards

SLDC- State load dispatch centre

STPM- Short term power market

STU- State transmission utility

SVM- Support Vector Machine

TAM- Term ahead market

T&D- Transmission and Distribution

TWh- Terra Watt Hour

UI- Unscheduled interchange

UPCL- Uttarakhand Power Corporation Limited

WBSEB- West Bengal State Electricity Board

TIC- Theil Inefficiency Coefficient

VAR- Vector Auto Regression

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CHAPTER 1
INTRODUCTION

1.0 OVERVIEW

The objective of this chapter is to identify the research area and to highlight the themes which have led to this study. The research showcased in the thesis includes the study of the global and Indian electricity market, reviewing of various ways in which trading in the Indian power market is conducted, identification of losses and risk assessment in the wholesale mechanism of electricity, and the determinants of the electricity prices which have led to the presence of high volatility in the exchange trade market. The study contributes to the existing body of literature by reviewing the need to conduct a study of volatility and forecasting methods in all the bid areas of the Indian electricity day- ahead market (DAM) which have never been conducted before thereby suggesting various tools for better modeling and forecasting of the DAM prices.

1.1 BACKGROUND OF THESIS

The Indian electricity market has experienced numerous variations since the last 10 years especially after the inception of power exchange in India. Even though trading through power exchange has a lesser risk, better efficiency, and liquidity, the volume traded is still low in comparison with other forms of trading i.e. long-term power purchase agreement (PPA) and short-term contracts. Most of the quantum of electricity is traded by / SEB's (state electricity board's) generators like the power generators, independent power producers (IPPs) and the distribution companies already have their energy tied up under long- term contracts leaving less scope of trading through short- term contracts.

Electricity as a commodity has different features in comparison with other commodities. It cannot be stored, has inelastic demand, restrictive transportation networks, kinked supply curve, and its prices are dependent on weather exhibiting annual, quarterly, monthly, weekly, daily, and intra-day seasonality not only in India but across the globe. All this makes electricity a highly volatile commodity in need of modeling and forecasting (as it is still a grey area for research) to help the stakeholders to take long or short positions in the market thereby leading to maximization of profits.

1.2 GLOBAL ELECTRICITY MARKET

Deregulation in the electricity markets in the 1990s and the liberalization of electricity trading has increased the importance of electricity trading in the short-term market. Since, electricity as a commodity(Barouti & Hoang, 2011) has certain peculiar features with non-storability being the most unique one, therefore various measures have to be taken in order to either provide storage or to manage it properly. The storage cost of electricity is generally very high, hence an introduction to price modeling and pricing of derivatives in the electricity market is a better option. Globally the electricity market is very mature (Srivastava et al., 2011). They have provided a platform to mitigate price risk risen due to increased volatility in the electricity markets worldwide and have made power trading a competitive and transparent process. Different electricity markets have adopted several market models over a period. Australia (NEMMCO- National Electricity Market Management Company Limited) and USA (PJM Interconnection LLC—Pennsylvania- New Jersey- Maryland Interconnection LLC) are the mandatory power markets whereas Nord Pool (Norwegian company), New Zealand (NZEM- New Zealand Electricity Market) and India (IEX – Indian Energy Exchange) are major voluntary marketplaces.

In Table 1.1 ((Mediratta, Pandya, & Khaparde, 2008), it has been observed that the European power market structure is advanced wherein it is simpler to establish new products. The flexible nature of the market necessitates a low level of system integration and easier transmission of pricing rules thereby making the European market model, an "easy to adopt" market model for the evolving markets. Both the European market and the Indian power market is also follows a decentralized market model. (Mediratta et al., 2008)

In the Indian power market, trading takes place as:

(i) Bilateral markets which include long-term, medium-term, and short-term contracts;
(ii) Multilateral markets which include trading through power exchange (IEX) and
(iii) Real-time multilateral balancing market i.e. DSM (deviation settlement mechanism).

1.3 INDIAN ELECTRICITY MARKET

The Indian electricity market has seen major changes since 1910 through several policies and regulations mentioned in Table 1.2 (Bhattacharyya, 2005; Mukherjee, Dhingra and Sengupta, 2017; The Indian Electricity Act, 1910; Indian Electricity Rules, 1956; Regulation 2004; The Electricity [Amendment] Bill, 2014; The Electricity [Supply] Act, 1948; The Electricity Laws [Amendment] Bill, 1991; The Electricity Regulatory Commissions Act, 1998; Trading License Regulation 2005; Zeyauddin,n.d.)

Earlier the electricity sector had a vertically integrated private or public monopoly market structure, which transformed into a competitive wholesale and retail mechanism with various reforms in the sector. The advent of these reforms has led to promotion of competition, thereby making the electricity market more efficient, liquid, and transparent (Ahmad & Alam, 2019) leading to an increase in the number of private players and change in the electricity pricing pattern.

Particulars	Nord Pool (Europe)	PJM (USA)	NEMMCO (Australia)	IEX (India)
Year of Inception	1991	1998	1996	2008
Participation	Voluntary day-ahead and adjustment market	Mandatory day-ahead market	Mandatory	Intended
Market Offerings	Day-ahead market, spot hourly, forwards, futures and options	Day-ahead spot, real-time balancing, capacity credits market	Day- ahead	DAM/TAM (Term-ahead market), REC (Renewable energy certificates),- ESCerts (Energy saving certificates)
Bidding Type	Buyers and sellers included	Buyers and sellers included	Buyers and sellers included	Buyers and sellers included
Adjustment Market	Elbas market: intraday auction market	Bid quantity can be changed anytime till the closing of the bidding	-	NA
Pricing Rule	Zone based	Nodal- based pricing	Zone- based	Zone- based
Pricing Type	Based on future events	Based on past events	Based on past events	Based on future events
Risk Management	Forwards, futures, and options	Financial transmission rights, bilateral, over the counter, multi-settlement market, virtual bidding, financial trading @ NYMEX	Bilateral, over the counter, derivatives on Sydney futures exchange	Bilateral, over the counter, and future market
Congestion Management	Market splitting	Security constrained economic dispatch	Locational signals for transmission tariff	Market splitting
Transmission Losses	Included in zonal prices	Included in LMP (Locational margin pricing)	Borne by generators	Borne by participants
Time blocks	Hourly blocks	Hourly blocks	5-minute blocks	15- minute blocks

Table 1.1: A comparative study of the global electricity exchanges

Act/Regulations	Objectives
IEA (Indian Electricity Act), 1910	Introduction of privatization in the electricity market
ESA (Energy Storage Association), 1948	Provision for state involvement
ESA, 1956	Changes in the ESA, 1948
IEA, 1991	IPPs came into the picture to generate electricity and sell to the Discoms through long term PPAs
ERCA, 1998	Developed distribution companies at the state level
IEA Act, 2003	Promoted electricity as a distinct commodity leading to more competition and efficiency in the power market
Open Access Regulations, 2004	The short term open access of various facilities was given on payment
Regulations, 2005	Provided regulations for procuring license for trading
Guidelines, 2006	To provide guidelines for bidding promotion of competition
CERC OAR, 2008 & 2009	Defined power exchanges, transmission charges/ wheeling charges, and losses in India
Power market regulations, 2010	Provided the method of trading power in India through traders and the procedures to become a power trader as well as the price discovery mechanism of power exchanges
Electricity (Amendment) Bill, 2014	Amendments to promote competition, bring efficiency in operations, and to improve the quality of supply of electricity
5th Amendment regulations, 2016	Procedure of segregation of the transmission charges and losses state- wise

Table 1.2: Regulations that led to the changes in the Indian electricity market

In India, the power market is segregated into five regions with different supply and demand conditions (as shown in Figure 1.1 (Shukla and Thampy, 2011)) thereby leading to huge demand-supply gap in the electricity market at geographical level i.e. power deficit (northern, western, and southern) in certain regions and power surplus in other regions (eastern and north-eastern). Hence the requirement for electricity trading is inevitable.

With reforms and advent of power trading as a distinct activity, although there is a decrease in the power deficit from 12.7% in 2009-10 to 1.6 % in 2016-17 (Central Electricity Authority, 2016-17) shown in Figure 1.2 below, still, the market is not mature enough in comparison with the global electricity markets. Compared with countries in Europe, where volumes traded on short-term markets range from 23 % to as much as 88 % as of 2015, short-term power markets account for meager 10 % of total electricity generation as on 2016-17 in India. As shown in Figure 1.3, the total electricity generation has augmented from 768.4 BU (Billion Units) in 2009-2010 to 1159.8 BU in 2016-17 with a share of short- term transactions of electricity as a percentage of total power generation rising from 9% in 2009-10 to 11% in 2011-12 till 2013-14, again declining to 9% in 2014-15 and rising to 10% in the year 2016-17 (Central Electricity Regulatory Commission, 2008- 2017). The total volume traded on the Nord Pool Spot market in the year 2015 was 489 TWh, which was more than 80% of the total Nordic/Baltic consumption (Chaubey, 2016). Currently, though less volume of electricity is being traded in exchange focusing on the short-term demand of electricity, more agreements such as forward delivery-based contracts can be introduced to the market participants in the exchanges. This will expand the trading horizon and prove to be very efficacious in evolved markets, such as Nord Pool.

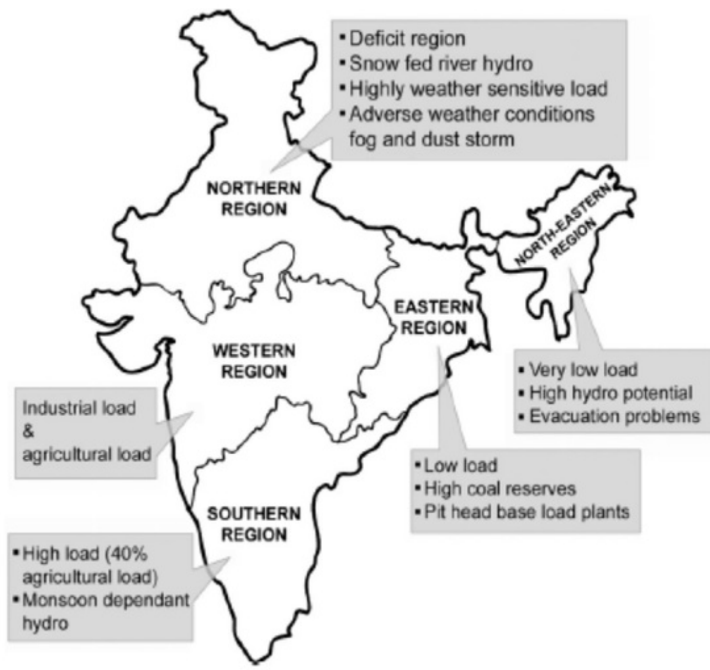

Figure 1.1: Supply and demand load in different geographical region

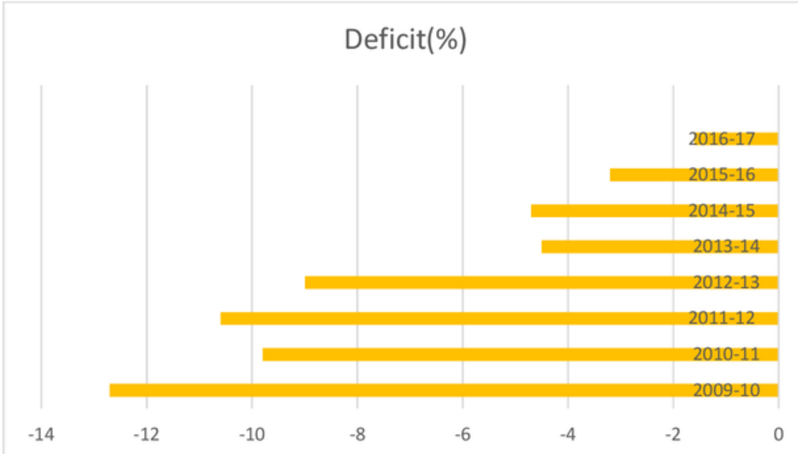

Figure 1.2: India's power deficit position in percentage

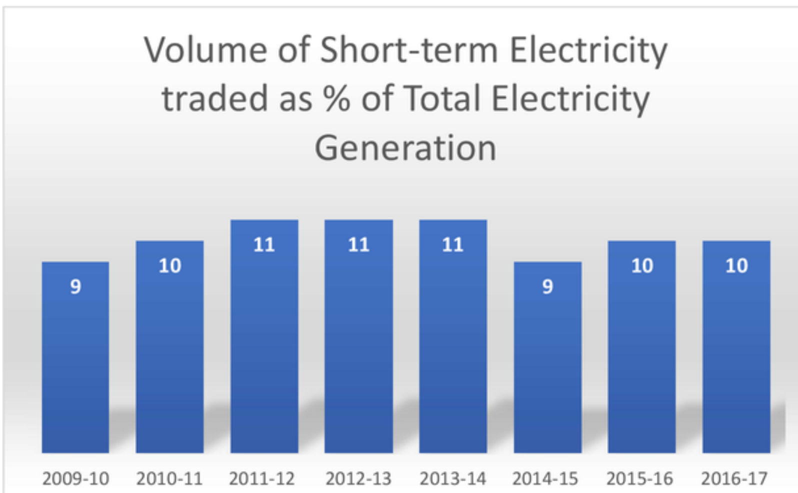

Figure 1.3: Volume of Short-term Electricity traded as % of Total Electricity Generation

In India, the major portion of electricity generated is obtained by long- term power purchase agreements between generating electric utilities and distribution utilities (shown in Figure 1.4 & 1.5). Long term contracts are generally bilateral contracts with a length of agreements ranging from 12 years to 25 years, with medium-term agreements ranging from 3 months to 3 years and the span of short-term contracts usually ranging between 15 minutes to 3 months (Sinha & Mathur, 2016). Over a period, it has been observed that the Gencos and Discoms are shifting from long- term contracts to short term or medium-term contracts (7-8 years) (Kujur, 2017).

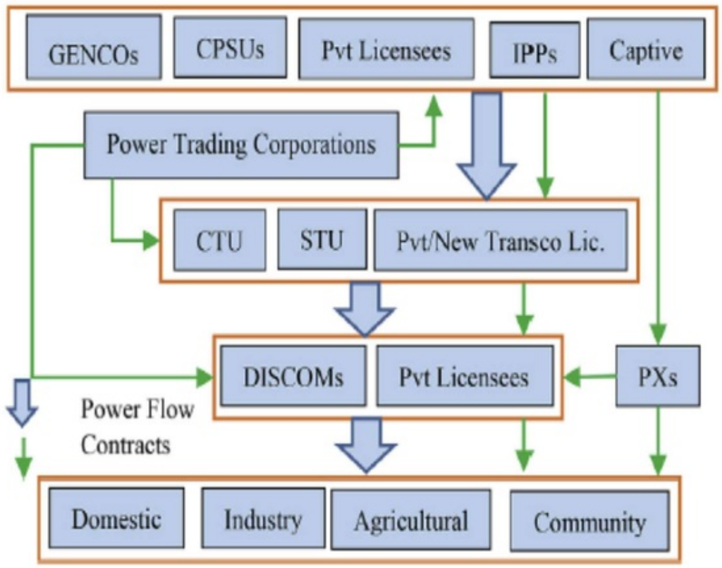

Figure 1.4: Flow of power contracts.

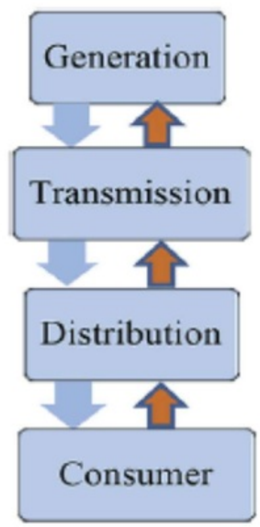

Figure 1.5: Vertically integrated market.

Since the market participants have shown a trend to shift from long- term PPAs to medium- term contracts a comparative analysis of both the contracts was conducted stating the various advantages and disadvantages of entering into both the contracts. The results are shown in Table 1.3 below (Jog, 2016; Sinha and Jain, 2017; Dewan, 2016; CERC, 2009b).

S. No.	Particulars	Long- term power purchase agreements		Short- term power purchase agreements	
		Advantages	**Disadvantages**	**Advantages**	**Disadvantages**
1	Tariff		Higher cost (mentioned in the Table 1.5.)	Lower cost	
2	Corridor booking	First preference			Last preference
3	Volatility	No fluctuation in tariff for long period			Governed by market forces (Girish et al., 2013)
4	Immediate requirement		Not fulfilled	Fulfilled due to presence of various products	
5	Price Analysis		Forecasting of prices difficult for long periods	Easier using volatility and forecasting tools	

Table 1.3: Advantages and disadvantages of short- term and long-term power contracts.

The table above clearly states that trading through short-term power purchase contracts is better than long- term contracts in terms of lower tariff, meeting immediate electricity requirement and conducting price analysis.

The table 1.4 clearly reflects that if the Discoms would have traded through IEX during the year 2016-17, they would have reduced their expenses incurred (State Distribution Utilities Fifth Annual Integrated Rating, 2017).

The Discoms would have saved around ₹3200 crore in FY17 (Sinha & Jain, 2017) if it would have bought electricity from exchange instead of PPA's given that the prices on the exchange were lower than the variable costs for multiple PPAs signed by state Discoms. Also, if we study the case of three Discoms (Uttarakhand Power Corporation Limited (UPCL), Assam Power Distribution Company Limited (APDCL), and West Bengal State Electricity Distribution Company Limited (WBSEDC) it has been observed that over a period with a

Discom	Long term power purchase cost (INR per kWh)	Market clearing price at the Indian Energy Exchange in the year 2016-17(INR per kWh) (IEX site)	Difference in prices (INR per kWh)
Ajmer Vidyut Vitran Nigam Limited	4.38	2.711	1.67
Chhattisgarh State Power Distribution Company Limited	3.89	2.711	1.18
Dakshin Haryana Bijli Vitran Nigam Limited	4.57	2.711	1.86
Eastern Power Distribution Company of Andhra Pradesh Limited	4.52	2.711	1.81
Himachal Pradesh State Electricity Board Limited	3.00	2.711	0.29
Jaipur Vitran Nigam Limited	4.28	2.711	1.57
Jodhpur Vidyut Vitran Nigam Limited	4.38	2.711	1.67
Meghalaya Power Distribution Corporation Limited	4.99	2.711	2.28
Northern Power Distribution Company of Telangana Limited	4.82	2.711	2.11
Southern Power Distribution Company of Andhra Pradesh Limited	4.76	2.711	2.05
Southern Power Distribution Company of Telangana Limited	4.55	2.711	1.84
Uttar Haryana Bijli Vitran Nigam Limited	4.65	2.711	1.94
Uttarakhand Power Corporation Limited	3.36	2.711	0.65

Table 1.4: Difference between the long- term power purchase cost fixed by the Discoms and the market clearing price in the IEX for the year 2016-17.

shift from long- term power purchase agreements to short- term agreements, there has been a decrease in the AT&C (Aggregate Technical & Commercial) losses in the respective companies. Hence, Indian Discoms need to make a balanced blend of long-term and short-term contracts with the base load to be met by long term and the surplus by short term in order to reduce their losses.

1.4 RISKS INVOLVED IN ELECTRICITY TRADING

In the short-term market, there are various financial risks involved such as (Industry Information Insights, 2014):

Market Risk

One of the major risks in the electricity market is market/ volatility/price risk. This risk needs to be addressed so that the traders can devise profit maximization strategies.

Counter-Party Credit Risk

Major losses are incurred by the bilateral traders due to default in payment by the parties. In case of exchange, this risk is borne by the exchange itself, therefore, trading through the exchange is much safer in comparison to short term bilateral trading.

Liquidity Risk

If we talk about bilateral trading, a huge amount of money is blocked i.e. the transaction cost, whereas in case of IEX only the initial margin amount is paid to initiate trading. Hence liquidity risk is less in exchange as compared to bilateral trading.

Even if we do a price analysis of the electricity traded through power exchanges and the bilateral contracts (Figure 1.6 (Central Electricity Regulatory Commission, 2008- 2017)) it clearly signifies that it is lucrative for the power traders and participants to trade through an exchange.

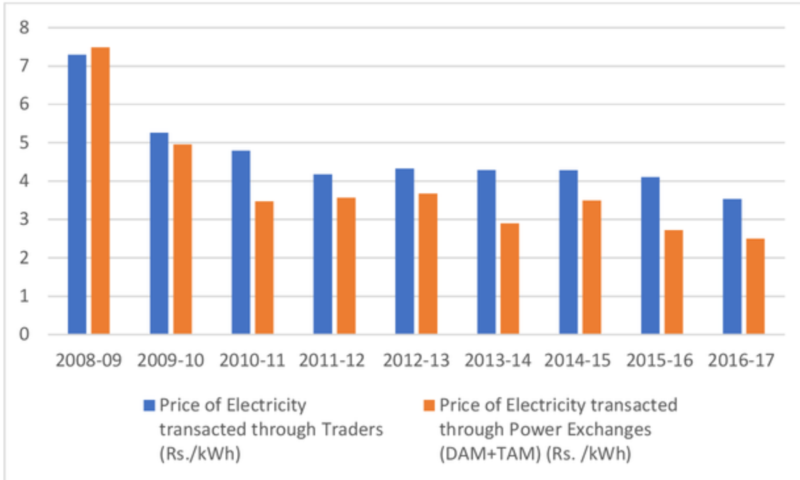

Figure 1.6: Price of electricity transacted through bilateral traders and power exchanges

From the above points, it can thus be concluded that trading through exchange is better in comparison to short- term bilateral market.

India has two electricity exchanges: Indian Energy Exchange (IEX) and Power Exchange India Limited (PXIL) which was formed on 27th June 2008 and 22nd October 2008 respectively (IEX and PXIL site). These exchanges cover all the five regions (northern, southern, western, eastern, and north- eastern) of Indian electricity market offering anonymous and automatic bidding, enabling effective price-discovery mechanism, risk mitigation strategies, and attempting to address the supply-demand gap. Between the two exchanges, IEX is a dominant player; hence the prices of IEX are taken for analysis.

IEX constituted meager 3.92 % of the total electricity traded (CERC Report, 2008-2017), despite the fact that prices of electricity traded in exchange have decreased making trading a profitable proposition (shown in Figure 1.7).

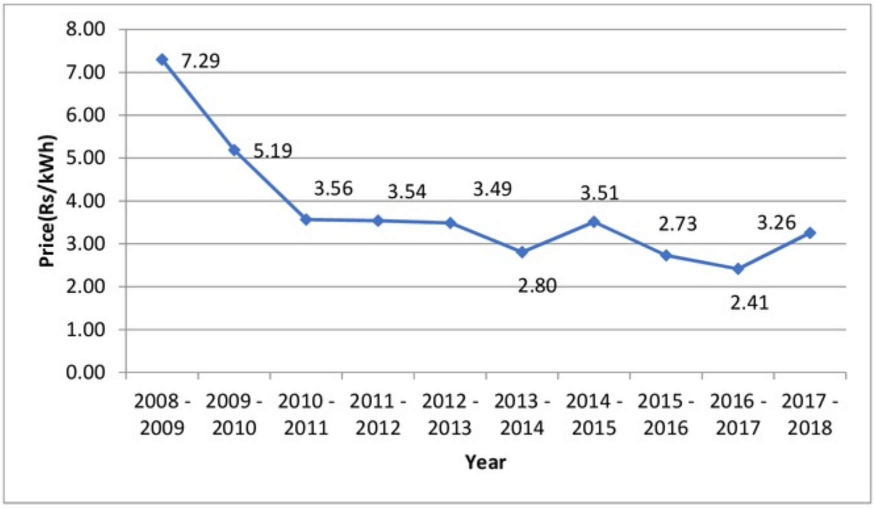

Figure 1.7: Market clearing price transacted through IEX.

IEX has further divided all the five regions mentioned above into 13 bid areas (shown in Table 1.5 and Figure 1.8 (Sinha, & Mathur, 2016; Ahmad & Alam, 2019;).to invite a greater number of stakeholders (captive power plants, industrial consumers, independent power producers, state private utilities) from each area to trade in the exchange.

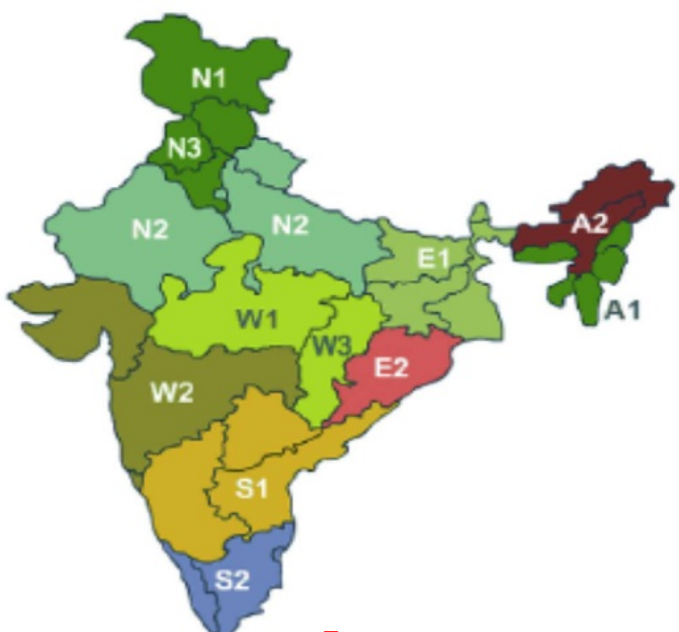

Figure 1.8: IEX bid areas

S.No.	Bid Area	Region	States
1	E1	Eastern	West Bengal, Sikkim, Bihar, Jharkhand
2	E2	Eastern	Orissa
3	N1	Northern	Jammu and Kashmir, Himachal Pradesh, Chandigarh, Haryana
4	N2	Northern	Uttar Pradesh, Uttaranchal, Rajasthan, Delhi
5	N3	Northern	Punjab
6	A1	North- Eastern	Tripura, Manipur, Mizoram, Nagaland
7	A2	North- Eastern	Assam, Arunachal Pradesh, Meghalaya
8	W1	Western	Madhya Pradesh
9	W2	Western	Maharashtra, Gujarat, Daman and Diu, Dadar and Nagar Haveli, North Goa
10	W3	Western	Chhattisgarh
11	S1	Southern	Andhra Pradesh, Telangana, Karnataka, Pondicherry (Yanam), South Goa
12	S2	Southern	Tamil Nadu, Pondicherry (Puducherry), Pondicherry (Karaikal), Pondicherry (Mahe)
13	S3	Southern	Kerala

Table 1.5: IEX bid areas

It has also been observed that there has been an increase in the bid areas; the reason behind it is to invite a large number of participants such as captive power plants, industrial consumers owning captive power plants, industrial consumers, independent power producers, state utilities, and private distribution licensees from each area to trade in the exchange.

IEX trades in four major products such as day-ahead market(DAM), term-ahead market (TAM), renewable energy certificates (REC), and energy saving certificates (ESCerts) with different years of inception (Figure 1.9 (Ahmad & Alam, 2019)). The DAM contract is a physical delivery market which offers bidding from both buyers and the sellers for delivery on the next day. The contract is entered into one day before the actual execution of the contract i.e. if the price and volume for a contract are determined on Thursday, then the contract will be delivered on Friday. Since DAM captures the major portion of IEX and trading takes place in 15-minute time blocks in 24 hours of the next day starting from midnight, therefore, conducting volatility analysis is easier in comparison with other products. In the DAM, the identity of the market participants is kept confidential (Ahmad & Alam, 2019; Sinha et al., 2016).

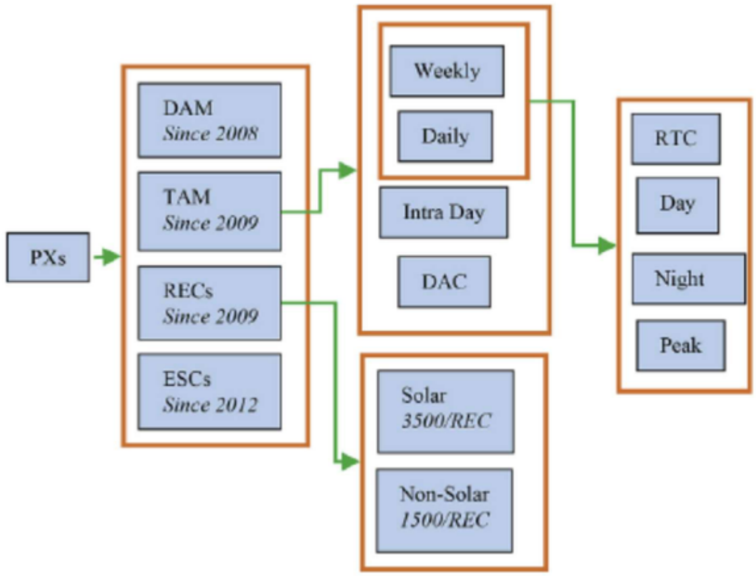

Figure 1.9: Layout of the electricity exchange contracts

Here, the buyer and the seller bids are entered with the buyer entering for the consumption of electricity at the cheapest price and the seller for selling at the maximum price. The time slot for bids is from 10 am to 12 noon with revision or cancellation possible only till 12 noon.

After the session, the exchange prepares a demand and a supply curve with a price on the Y-axis and quantity on the X-axis to calculate the market clearing price (MCP) in Rs. /mwh and market clearing volume (MCV) in MW (megawatt) for that day of all the bid areas (Figure 1.10 (Sinha et al., 2016)). Once the prices are set, participants of the exchange are informed regarding their fully or partially traded contract. Also, the details regarding the unconstrained volume and the congestion scenario in the transmission lines is shared for billing purpose.

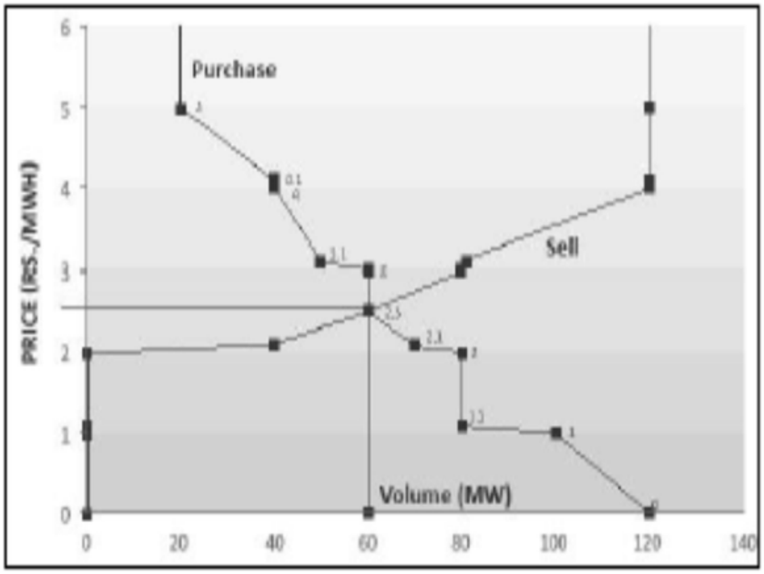

Figure 1.10: Demand-Supply curve to determine MCP and MCV

Once the settlement funds of each member and the required capacity available with the national load dispatch centre (NLDC) are checked, new bids are made at 1430 hours, based on which final market clearing price and volumes are decided by the electricity exchange. If the congestion is present in the grid, then its mitigation is done by splitting the market into various zones and the average clearing price for each zone is decided. After receiving the results, final obligations are sent to banks for payment to be made by the retailers for the consumption of electricity. The final results are further sent to the NLDC for confirmation and application of collective transactions. The contracted volume of electricity is now scheduled for delivery on the next day. The DAM trading process at IEX is explained in Figure 1.11 (Sinha et al., 2016) below.

The exchange as mentioned above has segregated its activities into 13 bid areas with the minimum bid of Rs.1 per 0.1 MWh. There are two types of bids which are done on the exchange such as single and block orders. Single bids are 15-minute bids with various pairs of price and quantity with partial or full execution of the bids entered by the stakeholders. Block Orders include bids of 15-minute blocks during the same days with no provision of partial execution by the market participants at the IEX.

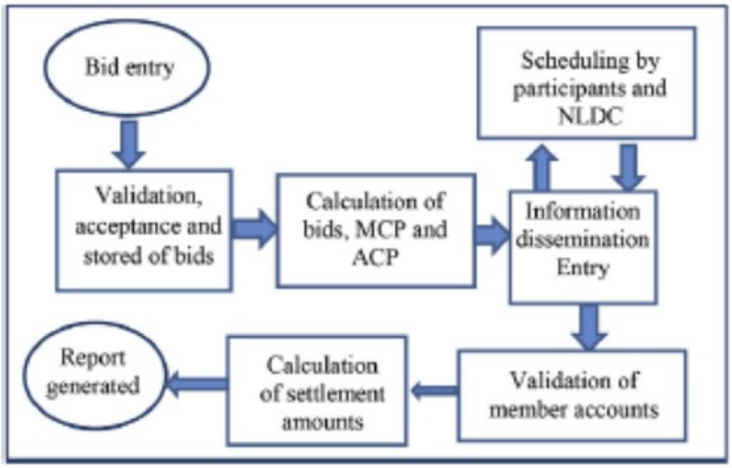

Figure 1.11:Trading process at the Day-Ahead Market

In IEX DAM, there are rapid movements in the prices ranging from as low as 43.5% in September 2009 to as high as 78% in March 2010 (author's own analysis). Though trading through the exchange is a better option with an increase in volume traded over a period of time (See Figure 1.12 (CERC, 2008-17) and exposure to a lesser number of risks and lower cost involved, still, the existence of high volatility clustering has led to a huge financial impact on the stakeholders.

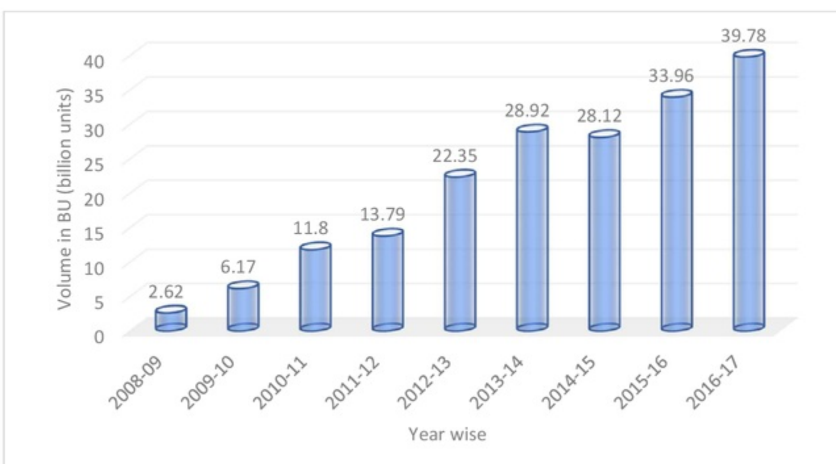

Figure 1.12: Volume traded at the IEX under Day-Ahead Market in India

A random comparative price analysis (bid area wise) of IEX with short-term bilateral contracts was conducted during May 2017 (May being one of the most volatile months of the year due to the summer season). The data of bilateral contract was taken from Form IV of power trading companies with Chandigarh, Delhi, Punjab, Chhattisgarh, Maharashtra, Tamil Nadu and Kerala, and Karnataka and Telangana being the delivery point for N1, N2, N3, W3, W2, S2, and S1 respectively. It has been observed that due to high volatility, the stakeholders incurred huge losses ranging from as low as Rs. 0.02 per kWh in N2 to as high as Rs. 0.51 per kWh in N2 except in S1, which observed profit despite of high volatility (See Figure 1.13 below).

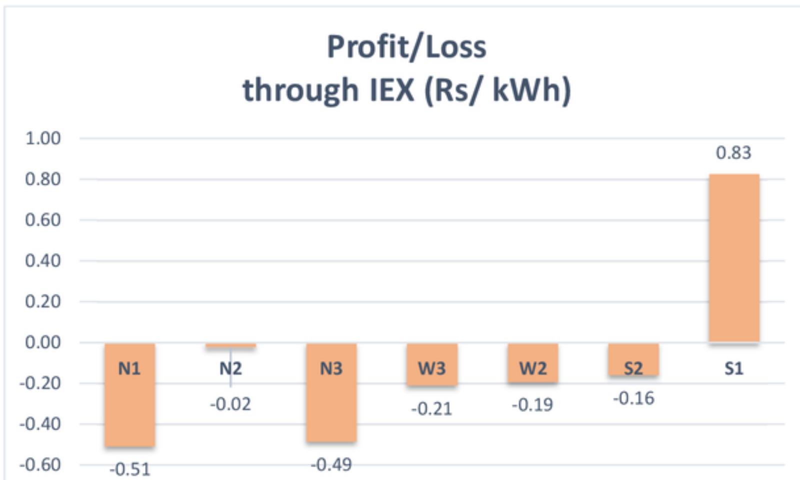

Figure 1.13: Bid area- wise profit/ loss through IEX (Rs./kWh) (author's own analysis).

All the above features of electricity (high spurts and volatility clustering and heavy losses caused to the market stakeholders) have led to the study of identification of the fundamental factors behind this erratic price movement with the application of mathematical modeling thereon.

1.5 DETERMINANTS OF THE ELECTRICITY PRICES

Electricity as a commodity is a peculiar commodity. Robert and Mount, 1998 stated various characteristics of electricity which qualitatively differentiated it from other commodities. The features of electricity are as follows:

- Lack of storability: Electricity storage is a costly process, leading to higher price volatility.

- Inelastic demand: Electricity has an inelastic demand i.e. not much effect on the demand patterns with the short-term fluctuations in the electricity spot prices (Robert and Mount, 1998).
- Restrictive transportation networks: The transmission network is a huge hurdle not only in India but across the globe, even if the countries have generation plants but many are lying idle because of lack of proper transmission networks (Bernard et al., 1998; Duckworth et al., 1998; Girish, Vijayalakshmi, 2013).
- Kinked supply curve: Existing generation plant produces a supply stack which becomes steeply sloped as maximum generating capacity is approached. When the generators reach their maximum capacity, due to inelastic demand, this produces large price movements for even the slightest change in demand when system generators approach maximum capacity (Frank and Patrick, 1997; Mount, 1999).
- Load relies on weather: Electricity load is dependent on weather conditions, often generating high load. This leads to difficulty in making precise forecasts.

All the above characteristics of electricity make it a volatile commodity and its forecasting a tedious task in comparison with other commodities.

Electricity prices generally exhibit seasonality at the annual, monthly, weekly, daily, and intra-day level not only in India but across the globe (Girish and Vijayalakshmi, 2013). Especially if we observe the IEX prices of each region, i.e. northern, southern, eastern, western, and north- eastern, each region has displayed uniqueness in its volatility patterns. The seasonal behaviour is shown collectively, but if we delve deeper into each region, a completely different picture comes out (author's own analysis: data collected from IEX site) (Indian Energy Exchange, 2017).

CERC's (Power Market) Regulations, 2010 has laid down certain rules on the basis of which the electricity trading market functions have made it mandatory for the exchange to disseminate price sensitive information to the general public so that electricity price modeling and its forecasting of electricity is made easier.

Across the globe, various studies have been conducted applying econometric models such as in Ontario (Sandhu, Fang and Guan, 2016), Europe (Hellström, Lundgren and Yu, 2012; Erdogdu, 2014; Frömmel, Han and Kratochvil, 2014; Mayer, Schmid, and Weber, 2015; Borovkova and Schmeck, 2017), USA (Dias and Ramos, 2014; Efimova and Serletis, 2014), Australia (Manner, Turk, and Eichler, 2016), and also in India (Girish, 2013; Ghosh and Kanjilal, 2014; Sinha and Mathur, 2016; Anamika and Kumar, 2016), but very few have identified the real reasons behind the fluctuation in the prices.

In India, various factors affecting the prices of electricity (Girish and Vijayalakshmi, 2013) have been found which are categorized as follows:

(a) Fundamental factors like fuel prices (i.e., coal, oil, gas), weather, temperature, precipitation, rainfall, time indices such as the days, weeks, months, and years, reservoir levels, and the cost of production of electricity per unit
(b) Operational factors like power load, power generation levels (deficit/surplus), congestion in the transmission grid, power system operating condition, and planned or forced outages in the power plants or transmission lines
(c) Strategic factors like power market design, power purchase agreements, bilateral contracts between the stakeholders, electricity exchange, and bidding strategies implemented by market participants
(d) Age- old factors like prices and demand

In order to identify the major factors affecting the prices in the DAM of the Indian Energy Exchange, firstly yearly data was studied. It has been observed that some bid areas have faced most volatility over a certain period, whereas there were other areas, which also have observed periods of constant volatility until the date. It has been illustrated in Figure 1.14 that prices in eastern region saw most volatility during 2008-12, whereas prices in northern region had a volatile period from 2008- 10 and again from April 2014- November 2015. Years from 2008 to 2013 have marked maximum volatility for the prices in the north- eastern region and the years from 2008-14 for the W1 & W2. The bid areas W3 and S1 have been facing continuous volatility since inception whereas the bid areas S2 & S3 had the highest degree of volatility since inception until April 2016.

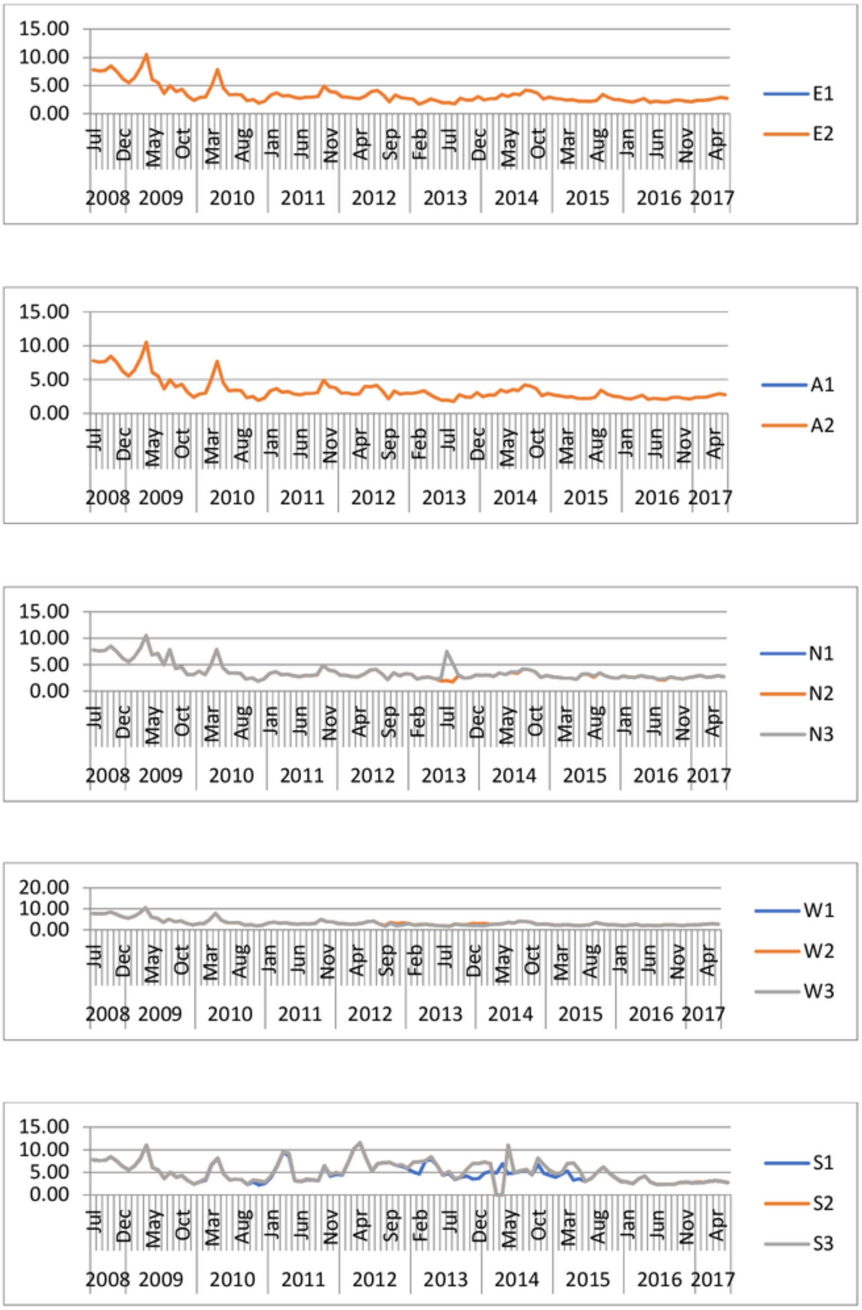

Figure 1.14: IEX monthly Day-Ahead prices (Rs./kWh) from 2008-17 of all 13 bid areas region- wise(author's own analysis).

The above analysis confirmed the presence of high volatility and led us to delve deeper into studying the monthly data of the day- ahead prices. The data were studied to observe the presence of seasonality, i.e. similar trends over the months in different regions. It was concluded that the eastern, north- eastern, western, and northern regions showed no monthly seasonality whereas the southern region displayed seasonality only in the months of March, May, and June. Since the presence of monthly seasonality is very less, therefore, the actual reasons behind the monthly price movement in the DAM are studied to get a clear picture of the factors. Various monthly and daily reports on electricity market published by the IEX (Indian Energy Exchange, 2017), Central Electricity Authority (CEA) (Central Electric Authority, 2006-2017), and Central Electricity Regulatory Commission (CERC) (Central Electricity Regulatory Commission, 2008- 2017) were referred in order to narrow down the above mentioned factors into few majors ones leading to the periods of spikes and jumps in the prices of IEX's DAM (See Table 1.6 below).

The table below reflects the reasons for fluctuations (monthly basis) in the electricity prices in the DAM of Indian Energy Exchange.

Year	Month	Event Occurred	Reason
2008	October	Increase by 10 %	Increase in the number of players in the market. News regarding CERCs price cap to cripple energy trade (Singh, 2008; Mishra, 2008)
	November	Fall by approx. 11 %	Introduction to a new product (TAM) in the Exchange. CERC reduced the limit of trading to 1mw (Business Line, 2008; Express News Service, 2008)
	December	Increase by approx. 16%	PTC India Ltd. to form joint ventures with power generation companies thereby increasing volume in the exchange. Government readies blueprint for the world's first energy savings market. CERC postponed the cap on the prices of inter-state short-term sale. (Financial Express, 2008; Report, 2008; Indian Energy Exchange, 2008; Central Electricity Regulatory Commission, 2008)
2009	January	Fall by approx. 12 %	CERC issues Tariff Regulations for 2009-14 (CERC, 2009a)
	February	Increase by approx. 16 %	Less coal supply (CEA, 2009)

Year	Month	Event Occurred	Reason
	March	Increase by approx. 25 %	CERC issued regulation(draft) on grant of connectivity both long and short term access to the inter-state transmission lines, Increase in volume by 108% (CERC, 2009b)
	April	Increase by approx 35% in the southern region and 30 % in the rest of the regions	CERC issues a regulation on Unscheduled Interchange (UI) Charges in 2009, General Elections (CERC, 2009c)
	May	Fall by approx 44 % in the southern region and 42 % in the rest of the regions	Power prices decrease by 39% due to increase in KG gas supply. Congestion in NR periphery. Elections in southern region, respite due to good climatic conditions. Draft regulations on tariff for renewable energy, draft regulation on CERC amends the Inter-State Open Access Regulations (Mascarenhas, 2009a; IEX, 2009a; CERC, 2009d; CERC, 2009e)
	July	Fall by approx 30 % in the northern region and approx 34 % in the rest of the regions	Government plans to sell power from unallocated quota via exchanges. Grid indiscipline not to hit consumers. Delayed monsoon (CERC, 2009b; Jog, 2009a; Business Standard, 2009)
	August	Increase by approx 57 % in the northern region and approx 37% in the rest of the regions	Failure of monsoon, insufficient transmission capacity, and plant outages especially in the northern and north- western parts of the country. Increase in open access consumers in Punjab, Rajasthan, Tamil Nadu, etc. CERC issued regulation(draft) on grant of connectivity both long and short term access to the inter-state transmission lines, (CERC, 2009f; Business Standard, 2009; Business Standard, 2009; IEX, 2009b; Jog, 2009b, IEX, 2009e)
	September	Fall by approx 45 % in the northern region and approx 20% in the rest of the regions	CERC issues order on the ceiling of tariff to trade electricity through bilateral agreements and on power exchanges. CERC gives approval for IEX region-wise day-ahead contingency, daily, intra-day, and weekly contracts (CERC, 2009g; Deo, 2009)
	October	Increase by approx 11% in all regions	Draft CERC Power Market Regulation, 2009. Price cap on the price of power traded on exchange, CERC draft order on revision of UI charges and additional UI charges.(CERC, 2009h; CERC, 2009i; IEX, 2009c)
	November	Fall by approx 31 % in the northern region and approx 27% in	Draft CERC Regulation for REC Framework Implementation November rainfall (Atmanand, 2009; Mascarenhas, 2009b; CERC, 2009j)

Year	Month	Event Occurred	Reason
		the rest of the regions	
	December	Fall by approx .02% in the northern region and approx 24% in the rest of the regions	Capping on the price in exchange, congestion in NR (Jog, 2009c; IEX, 2009d)
2010	January	Increase by 16% overall with 22% in S2 and S3 region	Highest congestion especially in S2 and S3 regions. CERC notifies power market regulations. Also CERC announces Renewable Energy Certificate (REC) Regulation. Less coal supply, Tamil Nadu Electricity Board Unbundled (CERC, 2010a; IEX,2010; CERC, 2010b)
	February	NR fall by approx 17 % and S1, S2, and S3 increase by 13%,17%, and 17% respectively	CERC issued draft Indian Electricity Grid Code Regulations 2010, CERC issued a regulation (draft) on Sharing inter-state Transmission Charges and Losses, CERC issues Fixing of Trading Margin Regulation (CERC, 2010c; CERC, 2010d; CERC, 2010e)
	March	NR rose by 60%, S1 rose by 104 %, S2and S3 rose by 89.5%, and rest rose by approx 67%	CERC determines the Forbearance and Floor Price for the REC framework. Increase in the number of industrial open access consumers, increase in temperature in comparison to the past year trends (CERC, 2008-17; https://www.wunderground.com/, 2017; CERC, 2010f)
	April	Increase by 56% in the rest of the region whereas only approx 20% in the southern region	CERC notifies Indian Electricity Grid Code Regulations in 2010. CERC issues UI Charges (Amendment) Regulations in 2010, weather change (onset of summers in the northern region), coal supply lesser in rest of the region in comparison with southern region (CEA, 2006-17; CERC, 2010g; CERC, 2010h)
	May	Decrease by approx. 42 % in all the regions	CERC implements IEGC in 2010; pre-onset of monsoon; Dadri plant operational (CERC, 2008-17)
	June	Fall by approx 26 %	The onset of monsoon (Indian Meteorological Department, 2010)
	September	Fall by approx 30 %	The peak period price lower than the price during RTC(round the clock) and off-peak periods, due to lesser volume of electricity transacted during peak period (5.7 Million Units through hydro generation (CERC, 2008-17)

Year	Month	Event Occurred	Reason
	October	Increase by 37% in the southern region and rest by 8 %	Power plant outage, congestion in the market, market spitting adopted except southern region (CEA, 2010-11; AF-Mercados EMI, 2014)
	November	Decrease by approx. 25% in all the regions except by 5% in the S2 and S3 region	The outage in the northern region, JSW Energy commissions 300 mw unit in Maharashtra, AP Genco commissions Stage-I of Kakatiya Thermal Power Plant, REC approved, excessive rainfall in the western region (IEX, 2010-2017; NRPC, 2010-11)
	December	Rose by approx 20% in rest of the region whereas slid by approx 7 % in the southern region	Outage and congestion, incessant rainfall in the southern region (NRPC, 2010-11)
2011	January	Increase by approx. 45 % in all the regions	Congestion, power plant outage (NRPC, 2010-11)
	February	Increase by approx. 50 % in the southern region, decrease by 17 % in the northern region, increase by 10% in other regions	Nearing elections in the southern region IEX, India's topmost Electricity Exchange launches Renewable Energy Certificate on its platform Outage and Congestion (CERC, 2008-17; NRPC, 2010-11)
	March	Decrease in other regions by approx 14 % and hike by 47% in the southern region	Impact of RECs in the market elections in the southern region (CERC, 2008-17)
	May	Fall by 10% in the rest of the regions and approx 65% in the southern region	New power plant operational (IEX, 2010-17)
	October	Increase by approx 103 % in the southern region and 58 % in rest of the region	Flooding of coal mines in Orissa and strike in SR coal mines, new power plants operational (IEX, 2010-17)
	November	Reduction by 19% in the rest of the regions and 31 % in the southern region	Effect of new power plant operational in October 2011. ONGC's Tripura power plant to commence production soon (IEX, 2010-17; AF-Mercados EMI, 2014)
2012	January	Reduction by around 20% in the rest of the region and approx 5% in the southern region	Impact of REC and new power plants operational (IEX, 2010-17)

Year	Month	Event Occurred	Reason
	June	Decrease in prices in the southern region by approx. 30 % and rise by 23% in rest of the region	Delayed monsoon in the northern region whereas southern region experienced earlier monsoon (CERC, 2010i)
	August	Rise by 23% in the rest of the regions whereas decrease by 34% in the southern region and 5% in W1 region	Effect of Blackout in July 2012, Congestion in transmission lines and new power plants becomes operational (IEX, 2010-17; AF-Mercados EMI, 2014)
	September	Decrease by approx 25% in all the regions except the southern region	CERC issues suo-motu order to NLDC congestion in the southern region new power plants (CERC, 2008-17)
	October	Approx. 53% rise in other regions except for the southern region and W1 saw a decline of approx 7%	Congestion in the NEW and Southern Grid power plant operational in Andhra Pradesh and Maharashtra (IEX, 2010-17)
	November	Approx decrease by 13 %	New power plant operational, Regulatory (IEX, 2010-17)
	December	Increase by approx. 12 % in the northern and western region	Congestion in the NEW Grid (IEX, 2010-17)
2013	February	Decrease by 30 % in all the regions except the north-eastern region	Largest volume traded in the northern region (IEX, 2010-17)
	March	Prices rose by approx. 13 % in rest of the region whereas by 60% in the southern region	Heavy congestion in the southern region, coal supply shortage (CEA, 2006-17; IEX, 2010-17)
	May	Decrease by 13 % approx in every region except the W3 region	Decrease in the congestion due to increased wind generation in Tamil Nadu Less demand, more supply; Fuel shortages (IEX, 2010-17)
	June	Decrease by 18% in all regions except by 32 % in the southern region	Despite congestion, sell bids increased, hydro schemes cleared in April 2013 to increase the supply (IEX, 2010-17)

Year	Month	Event Occurred	Reason
	September	Increase in price by approx 48% in all the regions, decrease in N3 by 40 %, rise of 13% in the southern region	Heavy congestion in all the regions (IEX, 2010-17)
	December	Rise in prices by 19 % in the northern and western region and by approx 28 % in the north- eastern and eastern region	Extreme congestion (IEX, 2010-17)
2014	April	Overall rise by 19% in all the regions	Unavailability of transmission corridor despite huge generation in Chattisgarh, Congestion in all the regions (IEX, 2010-17)
	June	Rise in prices by approx. 19% in all the regions, the decrease in the southern region by 54 %	Delayed arrival of monsoon and soaring temperatures, the price in southern region is still high in comparison to rest of the regions (IEX, 2010-17)
	August	The rise in prices by approx. 19% in all the regions	Light rainfall and decrease in a hydro generation, coal and gas scarcities and rise in the agricultural load in some states (IEX, 2010-17)
	November	Decrease by approx 28 % in all the regions	Winter season, lesser demand (IEX, 2010-17)
2015	January	The decrease in prices by approx. 11% in all the regions	Winter season, lesser demand (IEX, 2010-17)
	September	Rise by approx. 30 % in every region	Scanty rainfall and increased temperatures led to an increase in the buy volume (IEX, 2010-17)
	October	Decrease by 17% in all regions except for 20% in southern region	Winters ease congestion in all the bid areas, increased generation in SR (IEX, 2010-17)
	November	Decrease by 11% in all regions except for 20% in southern region	Winters ease congestion in NR, increased generation in SR (IEX, 2010-17)
2016	March	Increase by 13% in the north- eastern region and ER, 41% in the southern region	Congestion in the inter-state transmission corridor (IEX, 2010-17)

Year	Month	Event Occurred	Reason
	April	Increase in prices by approx. 12% of all the regions except by 17 % in SR	Rising temperature and congestion in the transmission grid (IEX, 2010-17)
	May	Approx 23% decrease in the eastern, western, and north- eastern region, 33% in the SR	Sell bids more than buy bids, eased congestion in all the regions (IEX, 2010-17)
	September	Hike by 13% in the eastern, western, and north-eastern region and by 27% in the northern region	Excessive congestion, around 40% volume lost due to congestion (IEX, 2010-17)
2017	January	Overall rise by 8% in all the regions	Congestion (IEX, 2010-17)
	April	10% increase in all the regions except northern and southern region	CERC amends IEGC Regulations (IEX, 2010-17)
	Aug	Overall 25% rise in all the regions	High- traded volume and inter-state congestion increased by 11 % (IEX, 2010-17)
	Sep	Overall 30% rise in all the regions	High- traded volume and inter-state congestion (IEX, 2010-17)
	Nov	Overall 13% decrease in all the regions	Increase in coal supply due to government initiatives, lesser demand, and drop in temperature across northern India (IEX, 2010-17)
	Dec	Overall 15% decrease in all the regions	Increase in coal supply due to government initiatives, lesser demand and drop in temperature across northern India (IEX, 2010-17)
2018	Mar	Overall 24% rise in all the regions	Increase in demand associated with seasonal variation i.e. onset of summers and inadequate availability of coal with the thermal generators (IEX, 2010-18)
	May	Overall 17% rise in all the regions	Extreme summers, lesser accessibility of coal, low hydro and wind power generation in the southern and the western states (IEX, 2010-18)
	Jun	Overall 20% rise in all the regions	Proposed Amendments in the rules related to electricity which have been set in 2005 (IEX, 2010-18)

Year	Month	Event Occurred	Reason
	Sep	Overall 40% rise in all the regions	Increase in demand of electricity from western, eastern, and southern states and supply-side bottlenecks such as coal shortages, reduced hydro and wind generation (IEX, 2010-18)
	Oct	Overall 26% rise in all the regions	Increase in electricity from western, eastern, and southern states, lesser availability of coal, reduction in generation from wind and hydro-based plants, light rainfall in the southern states during the second half of the month (IEX, 2010-18)

Table 1.6: Factors creating volatility in various regions of the Indian Electricity Exchange traded market

Through the study, it has been witnessed that especially in the initial period of trading almost all the regions have faced a high degree of volatility due to infrequent trading activity and "learning-by-doing" behaviour exhibited by the power market participants (Girish, 2016), and in the year 2011 and 2012, the prices have been smoothened due to changes in weather and an introduction of RECs and increase in the number of new power plants.

In 2012, there was a blackout in the new grid, which led to a rise in prices by 23% in the northern region. Since then it has been observed that whenever there has been major volatility in the electricity prices, it has been due to congestion in the inter-state transmission corridor or due to lack of proper transmission capacity (especially observed in N3, i.e. Punjab) along with few other reasons such as weather changes, regulatory changes, fuel shortages, and new operational power plant.

Furthermore, with the introduction of DSM in place of UI (Unscheduled Interchange) after 2012 blackout, to tighten the grid frequency there has been a reduction in the monthly variation in prices over a period of time. It has also been observed that since August 2008, the maximum frequency of occurrence of volatility between 10-30% has been in all the regions except the southern region due to regulatory changes, less coal supply, congestion in the transmission lines and seasonal variations. The occurrence of volatility between 30-70% has taken place in the southern region due to regulatory and weather changes, transmission congestion, elections, power plant outage, and new operational power plants. Furthermore, there were two incidents in March 2010 and October 2011, which have led to a phenomenal rise in the IEX prices by 89.5% in S2 and S3 and 104 % in S1 due to regulatory and weather changes in March 2010 and by 103 % in the southern region due to flooding of coal mines in Orissa leading to strike in the coal mines respectively.

Hence among the various reasons behind the huge price movement mentioned in the existing literature, only a few govern the electricity market, i.e. regulatory, weather changes, transmission congestion, elections, power plant outage, fuel supply, and new power plants operational which are further classified into demand and supply factors (See Table 1.7 below).

Demand factors	Weather changes, regulatory, elections
Supply factors	Regulatory, transmission congestion, fuel supply, new power plants operational, power plant outage

Table 1.7: Demand and supply factors affecting IEX's DAM prices.

1.6 VOLATILITY AND FORECASTING ANALYSIS IN THE ELECTRICITY MARKET

In a current deregulated scenario and observing the peculiar features of electricity, the study of volatility and forecasting of electricity demand and price interests the electricity stakeholders (Bunn, 2000). According to Weron (2006) & Weron and Misiorek (2005), if the traditional definition of volatility (i.e., standard deviation from the mean) is taken and measured on the daily basis, it is found that there is a presence of less than 0.5% volatility in the treasury bills and notes, Stock indices having reasonable volatility of around 1-1.5%, commodities such as crude oil and natural gas have volatility ranging from 1.5-4%, highly volatile stocks have volatility not exceeding 4%, and electricity prices exhibit very high volatility of up to 50% in the global market(Girish and Vijaylakshmi, 2013).

Even the prices in the Indian Energy Exchange's DAM reflects a high level of volatility and extreme spurts ranging from as low as around 7% in the year 2013-14 to as high as more than 20% in the year 2008-09 (See Table 1.8 (Central Electricity Regulatory Commission, 2008-17) below).

The power generator's revenue and suppliers' cost are affected due to high volatility in the prices. Risk management plays a vital role in managing energy commodity portfolios. Similarly, while application and valuation of the derivatives, modeling and forecasting is required, extremities affect the option values. Power market stakeholders such as industry professionals, regulators, and other participants are concerned about the huge spurts in the prices as it would lead to regulatory failure as well.

Volatility (in %)	
Year	**Indian Energy Exchange**
2008-09	more than 20%
2009-10	18
2010-11	11.97
2011-12	9.4
2012-13	9.3
2013-14	7.16
2014-15	9.63
2015-16	10.52
2016-17	8.17
2017-18	11.1

Table 1.8: Volatility (%) in the prices of IEX's Day- Ahead Market

Many researchers and academicians have developed various tools and algorithms for load and price forecasting. Whereas load forecasting is at progressive stage with a mean absolute percentage error (MAPE) below 3%, price-forecasting techniques are still in their early stages of maturity. (Weron, 2014; Abdel-Aal, 2006). Hence this research will focus on the study of power price modeling and forecasting techniques.

As mentioned in (Weron, 2014), there are three types of forecasting horizons i.e.

(a.) Short-term Electricity Price Forecasting (EPF) are the forecasts which are conducted for a period from a few minutes to a few days ahead and is useful in DAM operations.

(b.) Medium-term time horizons vary from days to months ahead, and are used for balance sheet calculations, risk management, and derivatives pricing and

(c.) Long term EPF is done for months, quarters or years and is useful for investment profitability analysis and planning, such as defining the sites for further generation and the sources of fuel.

Study of each of the above forecasting time horizons play an important role and intense studies have been conducted on various methods of forecasting with strengths and weaknesses of each.

Some of the methods of modeling and forecasting in the electricity market (which have already been applied) are classified as follows:

- **Multi-agent (multi-agent simulation, equilibrium, game theoretic) models** are the models which firstly create a simulation between the various units of the system (generating units, companies) networking with each other and then a price process is built by matching the demand and supply in the market. Nash- Cournot, supply function, strategic production cost, agent-based models are some of the highly used multi-agent models to forecast electricity. Ventosa, Baíllo, Ramos, and Rivier (2005) in Energy Policy discussed the different methods to model the participant's bidding behavior in the electricity markets, including the Nash-Cournot framework and the supply function equilibrium approach. Bunn (2000) found these methods to be inaccurate. Also, Koritarov (2004) and Weidlich and Veit (2008) have failed to find agent-based wholesale electricity market models relevant. Although being flexible tools to study the behavior of the power market participants, some of the components are required such as the players, their probable strategies, the ways in which they interrelate, and the set of payoffs. Hence the model mainly considers qualitative issues rather than quantitative results, Hence a complicated process.
- **Fundamental (structural) methods** explain the effect of vital physical and economic factors on the power market prices. Parameter-rich fundamental models and parsimonious structural models are the most popular types.

According to Carmona and Coulon (2014) and Barlow (2002), the model lacks practical implementation. As Borak and Weron (2008) and Fleten and Lemming (2003) also concluded that these methods, being tedious, are suitable for medium-term price forecasts not for short term. Also, these methods require various hypotheses about physical and economic relationships in the trading platform, which again requires lot of adjustment in the data if there is change in the market forces.

- **Reduced-form (quantitative, stochastic) models** are the models which study the statistical features of the power prices of electricity prices over a period with an aim of derivatives evaluation and risk mitigation. Jump-diffusion and Markov Regime Switching (MRS) models are the most popular ones. The methods such as mean-reverting jump-diffusions (Weron and Misiorek, 2008) or MRS models (Misiorek et al., 2006) for short- term forecasting i.e. the next day's hourly prices are considered to give inferior results. Also, Bessec and Bouabdallah (2005) and Dacco and Satchell (1999), have questioned the competence of MRS models for forecasting electricity prices as a whole. Whereas, Kosater and Mosler (2006) have suggested that the quantitative methods are useful for medium-term forecasting of mean daily prices while studying the German EEX(European Energy Exchange) market. They have compared parameter switching MRS specifications with the mean-reverting diffusion and have found that the regime switching models are more accurate for a forecasting period ranging from 30 to 80 days but not suitable for a period lesser than that.
- **Statistical (econometric, technical analysis)** approaches are the methods which involve direct implementation of the econometric techniques for load and price forecasting. Similar day exponential smoothening, GARCH (generalized auto-regressive conditional heteroskedasticity) family, regression are some of the common types. Few authors have also classified the econometric models as technical analysis tools. Technical analysts check the future performance of an asset by looking at the various charts to identify patterns and do not give much attention to the assessment of an asset's intrinsic or fundamental value. While the efficacy and utility of technical analysis in financial markets is often probed, the methods have been tried

and tested in the various power markets, where the results have been quite accurate due to the presence of seasonality in electricity price movements during normal, non-volatile periods (Weron, 2014).

- **Computational intelligence (artificial intelligence-based, non-parametric, non-linear statistical) techniques**, which combine elements of learning, evolution, and fuzziness to form methods which help in measuring volatility and forecasting.

Feedforward neural network, recurrent neural network, fuzzy neural network, and support vector machines are its type. The main forte of computational intelligence tools is their capability to handle intricacies and non-linearity of the data series. Hence it is considered among one of the best methods of volatility and forecasting (Bessec & Bouabdallah, 2005; Dacco & Satchell, 1999).

After going through the above methods, application of tools from the GARCH, ARIMA and ANN (artificial neural networks) family are the best techniques for the study of volatility and medium-term forecasting of the IEX's DAM market's electricity prices.

1.7 RESEARCH MOTIVATION

A robust trading system is vital to encourage competition in the Indian electricity market. In India, the exchange trading market is still at an incipient stage, despite being the best option for innovation with lesser risk exposure and lower cost involvement than other methods of trading. But due to the presence of high volatility, a huge amount of losses is incurred by the power market participants such as power generators and distribution companies. Although few major factors affecting DAMs prices are regulatory, weather, fuel supply, transmission congestion; power plant outages/new plants operational, frequency and reservoir levels have been identified, but a study to model and forecast electricity prices is required.

The study will encourage the

- Traders to adopt risk management techniques in future and forward market

- Distribution companies to optimize their power purchase cost and managing peak demand
- Generators to make wise investment decisions i.e. whether to invest in the further generation of electricity or to curtail it.

Also, distribution companies in India have accrued losses equal to 4% of India's GDP (gross domestic product) and losses around Rs. 68,000 crore ($10 billion) annually (Patil, April 2017). Hence this would also contribute to the betterment of the economy.

1.8 RESEARCH QUESTION

Research Question 1: What is the intensity of volatility in the Indian electricity DAM?

Research Question 2: Is measuring the intensity of volatility the only measure of analysis?

Research Question 3: What could be the probable forecasting techniques that can be applied in the bid areas of DAM?

1.9 BUSINESS PROBLEM

The business problem as identified for this research is as follows:

Factors affecting the prices (Regulatory, weather/ seasonal, fuel supply, transmission congestion, power plant outages/new plants operational, frequency and reservoir levels) leading to volatility in the short-term DAM, is a price risk factor which has to be scientifically measured and predicted for smooth functioning of short- term market.

1.10 RESEARCH PROBLEM

Measurement of volatility and forecasting based on scientific modeling in the Indian electricity DAM with respect to the bid areas needs to be conducted to encourage the stakeholders to apply risk management strategies and devise profit maximization techniques thereon.

1.11 RESEARCH OBJECTIVES

The research objectives of the study are as follows:

- To study the volatility of the price in the DAM since its inception
- To do a comparative study of the two well-known volatility models, sparsely applied in the Indian electricity DAM
- To provide the accurate forecasting technique to be applied in the DAM.

1.12 OVERVIEW OF RESEARCH MODEL

The research model adopted to cater to the research questions is as illustrated in Figure 1. 15 below.

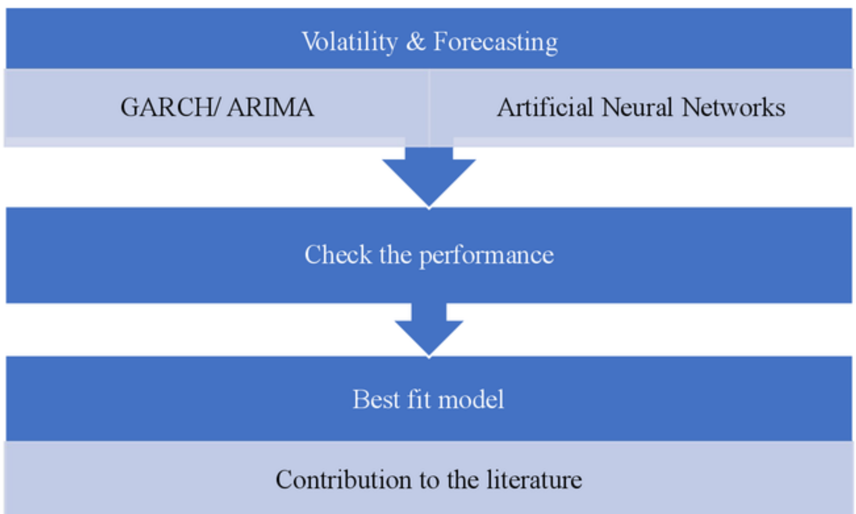

Figure 1.15: Research model for current research

The best fit model for GARCH & ANN depends on the lowest values of AIC (Akaike information criterion), BIC (Bayesian information criterion), SC (Schwarz criterion), and RMSE (Root mean square error).

1.13 OVERVIEW OF RESEARCH APPROACH

To meet each of the objectives of the research, Quantitative approach is followed which is mentioned below.

For RO1: Apply econometric model for capturing the data based on volatility (GARCH)

For RO2: Apply models from GARCH family to check the best fit model

For RO3: Conduct forecasting of the electricity prices (GARCH/ ARIMA family/ANN)

1.14 CONTRIBUTION OF RESEARCH

There are different ways research can be approached. This research focuses on the means with which volatility and forecasting assessments were made particularly in the Indian Energy Exchange market. Electricity prices generally exhibit seasonality at the annual, monthly, weekly, daily, and intra-day level not only in India but across the globe (Girish and Vijayalakshmi, 2013). In the current deregulated scenario and observing the peculiar features of electricity, the study of volatility and forecasting of electricity demand and price is a matter of interest to market participants (Bunn, 2000). According to Weron (2006) & Weron and Misiorek (2005), there are various methods through which the study of volatility and forecasting can be conducted but there has been no research till date (according to my study) which caters to the modeling of each bid area in the Indian Electricity Exchange market. The study of each bid area is vital as there are separate reasons which have led to volatility in each. This research would help the market participants such as power generators, distribution companies, power traders, and the transmission companies to have an efficient flow of power with maximization of profit.

1.15 OUTLINE OF THESIS CHAPTERS

The literature review in Chapter 2 throws light on academic as well as corporate reports on six themes such as global electricity market, Indian electricity markets, risks involved in electricity trading business, determinants creating price risk, volatility, and forecasting from which the gaps are identified and the research questions and research objectives are derived. The chronological order of research done, researcher(s), and their contribution are explained in the tabular form.

Chapter 3 outlines the research methodology based on the research problem, research questions, and its objectives. The current study employs quantitative methods (using statistical tools) applied to the data collected from secondary sources (from the India Energy Exchange site). A detailed explanation of each method is done (for volatility analysis GARCH[generalized auto-regressive conditional heteroskedastic] and EGARCH [exponential generalized auto-regressive conditional heteroskedastic] models are used and for forecasting ANN(artificial neural network) and ARMA (auto-regressive moving average) models are applied) in the chapter along with the analysis of the fitness of the best research model.

Chapter 4 throws light on the analysis of the result drawn from the models applied in the DAM of the Indian Energy Exchange. A detailed discussion of each model is done followed by their empirical results. The findings stated that GARCH is a better method to be applied for volatility analysis and ANN is considered to be a better method for forecasting electricity prices with reduced errors. These results can be used by the power market participants such as electricity generators, traders, transmission companies, and the distribution companies to mitigate their price risk and take wise investment decisions.

Chapter 5 finally gathers the information mentioned in the thesis and answers the research questions of the study posed in Chapter 1. It concludes the research by giving a summary of the research findings. The contribution of the research on the literature is also explained along with the limitations of the study and the scope of future research that has arisen from the current study.

Chapter 6 gives the details regarding the references used in the research in APA (American Psychological Association) style.

CHAPTER 2
LITERATURE REVIEW

2.0 CHAPTER OVERVIEW

The literature review covers the literature (both academic as well as corporate reports) referred to decide the topic of research. The literature review is segregated into six themes of the power trading market with admiration to the global electricity market, Indian electricity markets, risks involved in electricity trading business, determinants creating price risk, volatility, and forecasting. The six themes have been undertaken to identify the business problem. A funnel down approach was adopted to identify the gaps wherein the global electricity market and the Indian electricity market was studied to identify the area of research. In the Indian electricity market it was found that short term trading was still at an incipient stage and poses many risks (price risk being a major risk) which have led the researcher to delve deeper into the subject leading to the study of electricity price determinants, volatility models, and forecasting tools. This research aims to fill in the gaps in the existing literature by catering to the current research's questions and objectives. The chapter is broadly classified into five portions with literature on volatility, forecasting, all the six themes mentioned above structured in a tabular form constituting of the research done by various authors across the globe and in India and their individual contribution to the field of research, followed by gap identification and finally the conclusion of the chapter.

2.1 VOLATILITY

The term volatility is very much associated with stock markets, which are very highly unstable. This was very much prominent in the 1990s with unpredictable capital inflows associated with the capricious sentiment in the growing market segments. The term "volatile" could be applied to weather conditions like in many countries GDP is associated with good monsoons. This could also be related to the political climate where the oil prices could fluctuate due to change in governance. In the field of economics, volatility dates when the study of business cycles was started. However, the concept of volatility has started to progress into a unique topic in the area of macroeconomics over the last two decades and this has occupied a central position in today's development of economics. The prominence of volatility was brought by Valeri Ramey and Garey Ramey in the paper (Ramey & Ramey, 1995) where it was brought forward that volatility exerts a negative effect on growth over a longer period of time.

The best and early definition of volatility can be derived from Knight (1921) which states "Volatility is allied to risk in that it provides a measure of the possible variation or movement in a particular economic variable or some function of that variable such as growth rate." The concept is measured based on a study of a time series over a period. Volatility is commonly calculated by the deviation of the prices from the actual mean thereby leading to price risk, which can be derived from the residual of a forecasting equation for the whole variation in the data. The observation is that volatility tends to form a cluster and there could be a serial correlation in it. Hence the usage of ARCH(auto-regressive conditional heteroscedasticity) was one of the key contributions, which led to the award of Nobel Prize in 2003 to Robert F. Engle. A review of the journals present in the current literature explains the implementation of numerous econometric tools to study the day- ahead electricity prices of several power exchanges across the globe.

Volatility in Electricity Prices: According to Higgs (2009) and Walls (1999) various volatility models can be applied in the electricity markets across the globe.

- Random walk (Higgs, 2005)
- VAR (vector auto regression) Panagiotelis and Smith (2008) stated that VAR is suitable for linear data

- ARCH/GARCH (Generalized auto-regression conditional heteroscedasticity) (Lee and Hansen, 1994; Giraitis and Robinson, 2001)
- Mean Reversion and Regime-switching Models (Deng, 1998; Knittel and Roberts, 2005 and Escribano et al., 2011)

All the above-mentioned methods have been widely applied in the global power markets by various authors like Deng and Jiang (2005) who introduced Ornstein–Uhlenbeck stochastic model on power prices and have applied VAR for portfolio diversification in the US electricity market.

GARCH models and its alternatives, jump-diffusion models (Clewlow and Strickland, 2000; Deng, 1998; Knittel and Roberts, 2005; Seifert and Uhrig-Homburg, 2007) and the Markov regime switching models (Huisman and Mahieu, 2003; Kosater and Mosler, 2006; Becker et al., 2007 and Bierbrauer et al., 2007) have already been applied in foreign electricity markets. More work on this is presented below. Hadsell et al. (2004) applied a TARCH (thresholds auto-regressive conditional heteroskedasticity) model on the US wholesale markets to analyse volatility before and after the deregulation from May 1996 to September 2001. Park et al. (2006) have applied a VAR model to study the US local markets from 1998 to 2002. Hadsell and Shawky (2006) have conducted volatility study applying a GARCH model in the NYISO (New York Independent System Operators) day-ahead power market for peak period from January 2001 to June 2004. Higgs and Worthington (2005), ibid.(2008), and Higgs (2009) have studied the power prices in five regions of the National Electricity Market Management Company (NEMMCO), Australia and have applied normal APARCH (asymmetric power ARCH), student APARCH, and skewed APARCH to see the effect of news on the electricity prices. Christensen et al. (2009) proposed a Poisson auto-regressive framework and argued that persistence plays an important role while studying volatility. Le Pen and Sevi in the year 2010 have applied VAR-BEKK (BEKK named after Baba, Engle, Kraft, Kroner) model on the daily prices of the German, the Dutch, and the British forward electricity markets from March 2001 to June 2005 to check volatility spillovers between them. Schlueter (2010) applied a stochastic long-term or short-term model on the power prices of the four European markets such as German, Dutch, United Kingdom, and Nordic. Hellström et al. (2012) applied empirically (a mixed GARCH–EARJI jump model) to identify movement in prices of the Nordic electricity market. Dias and Ramos (2014) applied a regime switching with mean reversion model in the US wholesale market. Efimova and Serletis (2014) applied various univariate and multivariate GARCH models on commodities such as oil, natural gas, and electricity price using daily series of the US power market from the year 2001 to 2013. Frommel et al. (2014) have applied Realized GARCH-type models to conduct price jumps on the daily prices of the European Power Exchange.

Finally, Erdogdu, 2016 have applied Exponential or EGARCH and TARCH(threshold ARCH) models to analyse the leverage effect in the daily prices of the European electricity markets using data from 1992 to 2015 and have found that Russia, Poland, and the Czech Republic are the least unstable markets whereas France, Ireland, and Portugal are the most unpredictable ones. And the price variations have gone down over a period of time.

After conducting an in-depth analysis of all the above models, it has been observed that the GARCH model is considered to be better than other models in the foreign electricity market, thereby expanding the scope of this study. The GARCH family consists of various models, but the researcher shall test GARCH and EGARCH (exponential general auto-regressive conditional heteroskedastic) model on the data series to check volatility and the leverage effect of the Indian electricity exchange-traded market prices and select the best fit model which will contribute to the existing body of literature.

2.2 FORECASTING

Various methods and econometric techniques have been applied in the electricity prices across the globe and few in India too. An extensive literature overview of all the methods has been done by Weron (2006), Aggarwal et al. (2009), and Girish (2012).

According to them, all the methods were classified into five categories such as multi-agent models, fundamental methods such as parameter-rich fundamental models, and parsimonious structural models. Quantitative/stochastic models such as jump-diffusion and MRS (Markov regime switching) models, statistical (econometric, technical analysis) models such as similar day exponential smoothening, GARCH family, regression models, and computational intelligence techniques.

All these methods have been widely applied in the global markets.

For Spain and California day- ahead electricity markets, Contreras et al. (2003) have applied ARIMA (auto-regressive integrated moving average) technique to predict power prices.

Cuaresma et al. (2004) applied various models such as ARMA (auto-regressive moving average) processes with jumps and unobserved components model to predict the Leipzig Power Exchange's power prices from June 2000 and October 2001. The values of RMSE (root mean square error) and MAE (mean absolute error) was studied to conclude that ARMA model with jumps was a better model and had fewer errors.

Conejo et al. (2005) applied ARIMA, dynamic regression, and transfer function models on the PJM Interconnection's market clearing prices of the year 2002. They concluded that dynamic regression and transfer function algorithms are the better ones. Zhou et al. (2006) applied the ARIMA and extended ARIMA model on the hourly electricity prices of Californian Power Market. They found that the extended ARIMA model is an accurate method for price forecasting.

Huisman et al. (2007) studied the hourly prices of the Amsterdam Power Exchange, European Energy Exchange, and the Purchase Power Exchange of Paris in a panel framework and have found that day-ahead market's prices exhibit the characteristics of mean reversion and have a huge impact on the market.

Bowden and Payne (2008) also applied various models including ARIMA, ARIMA-EGARCH (Exponential GARCH), ARIMA EGARCH-M (ARIMA EGARCH-in mean) model on the hourly prices of five areas of Midwest Independent System Operator from 9th July 2007 to 6th August 2007 and have found that ARIMA EGARCH-M model has outperformed other models in out sample forecasting. Jakasa (2011) applied the ARIMA model on the German electricity market's day- ahead spot prices from 2000 to 2011 keeping seasonality component and workdays and weekend periodicity in mind. Kristiansen (2012) and Garcia and Contreras (2005) applied the ARX (auto-regressive exogenous) model with exogenous variables for Nord Pool and Spanish and California electricity markets.

Various authors have applied variants of GARCH model with a combination of ARMA to forecast electricity prices. Liu and Shi in the year 2013 forecasted the ISO New England market's day- ahead electricity prices from 1st January 2008 to 28th February 2010 applying models like ARMA GARCH in the mean model, ARMA-QGARCH, ARMA-SGARCH, ARMA-GJRGARCH, ARMA-EGARCH, and ARMA- NGARCH in the mean model and concluded that the first model is the most precise one.

Also, in the Indian electricity market, various papers on forecasting techniques have been published which are as follows: Girish, 2015 have applied various variants of GARCH in the five regions of IEX from 1 October 2010 to 30 September 2013, and found that ARIMA- PARCH(1,1) model had the most accuracy for the northern, eastern, and the north- eastern regions; ARIMA-GARCH(1,1) model was most accurate for the western region, and ARIMA-EGARCH model was most accurate for southern region. Girish and Tiwari, 2016 found that based on MASE (mean absolute scaled error) the ARIMA model, Nile theta forecast model, and ETS (error, trends, seasonality) models present smaller forecasting errors and thus better accuracy could be availed in each of the regions of IEX DAM market for a shorter period of time from 1 January 2010 to 31 December 2015. They suggested that more models from the GARCH family like APARCH and CGARCH can be applied to predict and model electricity prices and that too for a longer period. Sinha and Mathur (2016) have applied ARMA to study the effect of weekday and weekends on the prices of W2 region from 1 April 2010 to 31 March 2014. Hence other regions have been ignored. Ghosh, 2014 applied MSARIMA- EGARCH but for a very short period of time from 1 September. 2008 to 30 September 2008.

Looking at the current literature, a lot of scope of research lies in the IEX DAM in each of the bid areas. Also, if we talk about the application of ANN (artificial neural network) in the Indian sector, Nargale & Patil (2016) have applied Feedforward for a period of five days in the IEX and PXIL from 13th April 2010 to 18th April 2010, which has proved to be better than any other model and their MAPE (mean absolute percentage error) comes out to be 17%. Whereas Anamika & Kumar, 2016 did a comparative study of two models (Regression & ANN) on Indian Energy Exchange for the period January 2013 to March 2014 and found that Regression is a better model.

It is pretty much clear from the above literature that the time series method and computational intelligence outperform the other electricity price forecasting methods in case of short-term forecasting. Among the statistical methods/ Time series model, according to Agarwal et al (2009), parsimonious stochastic methods i.e. GARCH and ARIMA models are considered to be best for medium-term electricity forecasting considering the presence of seasonality, inelastic demand, and heteroscedasticity nature of the electricity (Bunn and Karakatsani, 2003).

Hence, the research will focus on the application of GARCH(1,1), best-fit models of ARIMA and NNAR(neural network auto-regression) model to predict the medium term electricity prices of the Indian electricity exchange-traded market.

Looking at the current literature, a lot of scope of research lies in the study of volatility and forecasting of the prices of the IEX DAM in each of the bid areas.

The rest of the Literature review (Theme- wise) along with gap is as follows:

2.3 CHRONOLOGICAL ORDER OF RESEARCH DONE AND RESEARCHER(S) AND CONTRIBUTION (TABULAR FORM)

Theme 1: Global Electricity Market

S. No	Title	Author	Year	Findings	Gap
1	Energy trading in the EU: Commoditization of electricity and the emergence of Energy Exchanges	Sabine Schulte-Beckhausen	2000	European Energy trading market is yet to flourish	More study on energy trading in Europe is required
2	Risk management in energy and power sectors: New developments in modeling, pricing, and hedging	Alexander Eydeland and Krzysztof Wolyneic	2003	A general overview of the electricity market structure	
3	Electricity trading in competitive power market: An overview and key issues	Prabodh Bajpai and S. N. Singh	2004	A comparative study of the Indian and some developed markets (UK, Nordic, and California electricity market). The challenges in the electricity trading markets are also critically analysed	The quality of electricity and demand side management are serious issues yet to be studied
4	Power markets across the globe and Indian power market	R. K. Mediratta, Vishal Pandya, and S. A. Khaparde	2008	A comparative study of IEX (Indian Energy Exchange) with Nord Pool, PJM (Pennsylvania, New Jersey, Maryland), and NEMMCO (National Electricity Market Maagement Company), of which the European market is easy to adopt	More study on IEX required
5	Electricity as a commodity	Mehdi Barouti and Veit Dung D. Hoang	2011	Three major characteristics of electricity, various markets in Nord Pool	Only a few countries of Nord Pool were referred

S. No	Title	Author	Year	Findings	Gap
				and how each market is different, pricing models in the Nord Pool, etc. Deregulation will lead to growth in the market	
6	A re-energized approach to a competitive European electricity market	Patrick Ryan	2015	Focusses on the three packages of laws that have led to a change in the European electricity market	Need to research if these packages will generate a successful pan-European electricity market
7	The benefits of integrating European electricity markets	David Newbery, Goran Strbac, Ivan Viehoff	2016	Market coupling benefits the European power markets by applying European Commission's Target Electricity Model (TEM)	Interconnectors should be remunerated
8	Electricity markets around the world	Klaus Mayer, Stefan Trück	2018	Electricity day- ahead markets are less volatile in comparison with spot markets	The results will help the market participants to forecast electricity further
Theme 2: Indian Electricity Market					
9	The Indian electricity market: Country study and investment context	Peter M. Lamb	2004	Studied the investment patterns of IPPs(independent power producers) in India: state- wise	
10	An electric power trading model for Indian electricity market	P. Bajpai and S. N. Singh	2006	The current electricity trading market is at a nascent stage. Proper settlement mechanisms and clear information regarding prices, sales, and	Power Exchange required to trade

S. No	Title	Author	Year	Findings	Gap
				trading volume are missing	
11	Analysis of competition and market power in the wholesale electricity market in India	Umesh Kumar Shukla, Ashok Thampy	2011	Various methods have been applied in the wholesale electricity market in India to check the market power. Market power leads to an increase in prices	Suggestions on reduction of losses given that can be applied by the government
12	Power sector reform and pricing of electricity: The Odisha experience	Shibalal Meher and Ajoy Sahu	2013	Study of the reforms in Odisha post-Electricity Act, 2003	
13	Spot electricity price dynamics of Indian electricity market	G.P. Girish and S. Vijayalakshmi	2014	Overview of various modeling and forecasting methods to study the electricity prices across the globe and its determinants	Forecasting techniques can be applied
14	Role of Energy Exchanges for power trading in India	G. P. Girish and S. Vijayalakshmi	2015	The emergence of future exchanges across the globe, the Indian power market at a nascent stage	A deeper study of the Indian power market is required
15	Competitive mechanisms in Indian power sector: Some reflections on trends and patterns	Gopal K. Sarangi and Arabinda Mishra	2015	The share of exchange-traded electricity is rising	The short-term electricity market is still to be explored with the transmission of electricity: a major problem
16	State distribution utilities fifth annual integrated rating	Ministry of Power	2017	Study the ratings and PPAs (power purchase agreements) of Discoms in India	
17	Assessment of power exchange-	Furkan Ahmad, Mohammad Saad Alam	2019	Overview of the Indian electricity market is given	

S. No	Title	Author	Year	Findings	Gap
	based electricity market in India				
Theme 3: Risks					
18	Managing electricity market price risk	Iivo Vehvilainen, Jussi Keppo	2003	Monte Carlo method is applied to the portfolio of the Nordic electricity market suggesting that risk mitigation tools can be applied on a daily basis	Price process models need to be studied further
19	Risk assessment in energy trading	R. Dahlgren, Chen-Ching Liu, and J. Lawarree	2003	Methods such as VARand Conditional VAR has been applied in various market situations	Modeling bidding behaviors of market players are to be studied, well-designed market rules required, the study of financial transmission rights (FTR) needs to be done
20	Managing the financial risks of electricity producers using options	S. Pineda, A.J. Conejo	2012	Payment risk: one of the the major risks in the electricity market, which can be mitigated through options	Future research on the possible correlations among the parameters such as pool and forward prices and unit failures can be done
21	Assessment of price risk of power under Indian electricity market	Sandeep Chawda and S. Deshmukh	2012	Study of the various risks in the electricity sector with focus on the risk mitigation of the price risk by using VAR and CVAR in	Other methods can also be applied

S. No	Title	Author	Year	Findings	Gap
				the Indian electricity market	
22	Power market and trading	Industry Information Insights	2014	Information regarding the risks in power trading in India	
23	Trading on Power Exchange: IEX	Indian Energy Exchange	2015	Study of the various risks in the Indian electricity markets	
24	2016 Annual Report	Nord Pool	2016	Study of the various risks in the electricity markets	
Theme 4: Determinants creating price risk					
25	Why did electricity prices fall in England and Wales?	John Bower	2002	Low fuel prices i.e. of gas and coal and policy failure affected the prices of England and Wales electricity market from 1st April 1990 to 31st March 2002	A study on the nuclear industry and Sottish market needs to be done
26	Central Electricity Regulatory Commission (Power Market) Regulations, 2010	Central Electricity Regulatory Commission	2010	Factors affecting the electricity prices	
27	Determinants of electricity price in competitive power market	G.P. Girish and Vijaylakshmi	2013	Stylized facts, review of forecasting techniques that can be applied in the Indian electricity market, determinants of the electricity market	Forecasting techniques yet to be applied
28	Electricity demand pattern analysis	Power System Operation Corporation Limited	2016	Factors affecting the electricity prices	
29	IEX Bulletin	India Energy Exchange official website	2008-2017	Factors affecting the electricity prices	

S. No	Title	Author	Year	Findings	Gap
30	Reports of the market monitoring cell	Central Electricity Regulatory Commission official website	2008-2017	Factors affecting the electricity prices	
Theme 5: Volatility					
31	Understanding price volatility in electricity markets	Fernando Alvarado and Rajesh Rajaraman	2000	Frequency-domain methods are better tools to measure periodic components of price variability	Only random study done, TOD concept ignored
32	Hedging with futures: Efficacy of GARCH correlation models to European electricity markets	Giovanna Zanottia, Giampaolo Gabbib, Manuela Geranioc	2009	Overview of European electricity market, the hedge ratio estimation model is useful to reduce the portfolio volatility. GARCH is useful when volatility is high.	Can be applied in the Indian market as well
33	Stochastic models of energy commodity prices and their applications: Mean-reversion with Jumps and Spikes	Shijie Deng	2000	Various mean reversion jump-diffusion models have been applied to the electricity spot prices in the US market	Econometric models required for better study
34	GARCH 101: The use of ARCH/GARCH models in Applied Econometrics	Robert Engle	2001	The analysis of ARCH (auto-regressive conditional heteroscedasticity)/ and GARCH(generalized auto-regressive conditional heteroscedasticity) models to get a clear understanding of the subject	Multivariate GARCH not covered

S. No	Title	Author	Year	Findings	Gap
35	Evaluating GARCH models	Stefan Lundbergh and Timo Terasvirta	2002	The research suggests that robust tests are better than non- robust models	GARCH methods are adequate ones
36	Day-ahead market price volatility analysis in deregulated electricity markets	Michele Benini & Marracci, M & Pelacchi, P & Venturini, A.	2002	Volatility study has been carried out in the electricity spot market prices of Spain, California, United Kingdom, and PJM from 1999 to 2000	Forecasting techniques can be carried out
37	Evaluating the informational efficiency of Australian electricity spot markets: multiple variance ratio tests of random walks	Helen Higgs and Andrew C. Worthington	2003	This paper examines the peak and off-peak daily prices of the New South Wales, Victoria, Queensland, and South Australian electricity market from July 1999 to June 2001 applying multiple variance tests. The Victorian off-peak period market is most efficient among all	Detailed analysis of each market should be done to get the real picture
38	Deregulated power prices: comparison of volatility	Ying Li, Peter C. Flynn	2003	The volatility of 14 electricity markets is studied, where some markets like Britain and Spain are predictable and consistent whereas South Australian and Alberta markets are unpredictable	Hedging strategies can be applied
39	Introduction to GARCH models in Time Series Econometrics	Bryant Wong	2004	A simple study of GARCH/ ARCH(auto-regressive conditional heteroscedasticity) model	Usage of more sophisticated tools

S. No	Title	Author	Year	Findings	Gap
40	Systematic features of high-frequency volatility in Australian electricity markets: Intraday patterns, information arrival, and calendar effects	H. Higgs and Andrew Worthington	2005	Various methods were applied to check volatility in the Australian market. The results suggested that asymmetric skewed student APARCH (asymmetric power ARCH) method is the best fit model	More variants of GARCH can be applied
41	The volatility of power markets	Ingve Simonsen	2005	The Nordic day-ahead electricity market for 12 years is studied. The observations conclude that there is consistency between the correlation in volatility and inverse power-law decay	Leverage effect not taken
42	Transmission of prices and price volatility in Australian electricity spot markets: a multivariate GARCH analysis	Andrew Worthington, Adam Kay-Spratley, Helen Higgs	2005	A multivariate GARCH model is applied on the five markets of the Australian National Electricity Market to study the price volatility spillovers suggesting that positive spillovers are present in only two markets whereas others don't have mean spillovers	Study of five electricity regions individually is required
43	Hourly electricity prices in day-ahead markets	Ronald Huisman, Christian Huurman, Ronald Mahieu	2007	The hourly electricity prices of Amsterdam Power Exchange (APX), the European Energy Exchange (EEX; Germany), and the Paris Power Exchange (PPX) are studied for 2004	Risk mitigation techniques and derivatives can be studied further

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				suggesting that volatility exists and a cross-sectional correlation pattern is present between the hours	
44	Modeling jumps in electricity prices: theory and empirical evidence	Jan Seifert and Marliese Uhrig Homburg	2007	The Poisson jump models are better than the Poisson spike method while studying the volatility in the daily electricity prices of EEX. Also, European options are more volatile than swing contracts	Swing contracts to be studied in detail
45	Modeling spot prices in Ukrainian wholesale electricity market	Sergui Frunze	2007	Applied GARCH, TGARCH (threshold GARCH), and EGARCH (exponential generalized auto-regressive conditional heteroscedasticity) model to study the prices of Ukrainian wholesale electricity market from January 2003 to 2007 suggesting high volatility and presence of leverage effect in the market	Forecasting techniques can be carried out
46	Modeling spikes in electricity prices	Ralf Becker, Stan Burn and Vlad Pavlov	2008	Applied regime-switching method on the Queensland electricity market suggesting that demand factors play a vital role in determining persistence in the data set	Forecasting techniques can be carried out

S. No	Title	Author	Year	Findings	Gap
47	Volatility transmission and volatility impulse response functions in European electricity forward markets	Le Pen Yannick and Benoit Sevi	2008	VAR-BEKK (Baba, Engle, Kraft, Kroner) model applied on the prices of the German, Dutch, and the British forward electricity markets from March 2001 to June 2005 suggesting that the spillovers exist between them	Study of high-frequency data can be done
48	On the leverage effect in the Spanish electricity spot market	J.M. Montero, M.C. Garcia, and G. Fernandez Aviles	2011	Applied various models to study the leverage effect in the prices of the Spanish electricity market suggesting that TA-ARSVA model outperforms the other models on the data set	Other models to check asymmetry not yet covered, such as APARCH
49	Modeling electricity prices: international evidence	Alvaro Escribano, J. Ignacio Pena, and Pablo Villaplana	2011	8 electricity markets studied applying the GARCH(1,1) model suggesting that huge volatility exists	Leverage effect can be studied further
50	Why do electricity prices jump? Empirical evidence from the Nordic electricity market	Jorgen Hellstorm, Jens Lundgren, and Haishan Yu	2012	The authors have applied a mixed GARCH-EARJI jump model on the prices of the Nordic electricity market suggesting that the market structure plays a vital role in studying volatility	Other models can also be studied
51	A comparison between different volatility models	Daniel Amskold	2014	GARCH models are difficult to apply due to variation in the results	The impact of implied volatility on calculating risk can be studied further
52	Energy markets volatility	Olga Efimova, Apostolos Serletis	2014	Univariate modeling better than multivariate	Various models can be applied to

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	modeling using GARCH				hedge market risk
53	Heterogeneous price dynamics in US regional electricity markets	Jose G. Dias and Sofia B Ramos	2014	Regime switching method applied to the US electricity market suggesting that there are fewer similarities between the markets giving different results	Dynamics of regimes can be studied further
54	Electricity market price volatility: The importance of ramping costs	Dan Werner	2014	Effect on natural gas prices on the electricity prices of the New England market is studied suggesting GARCH is an effective model	Effect of natural gas prices on electricity prices on an hourly basis can be studied in the future
55	Efficient modeling and forecasting of the electricity spot price	Florian Ziel, Rick Steinert, and Sven Husmann	2014	VAR-TARCH(thresholds auto-regressive conditional heteroscedasticity) model applied on the hourly prices of the EPEX incorporating renewable energy	More variants can be applied
56	On the determination of European day-ahead electricity prices: The Turkish case	Kursad Derinkuyu	2015	Model is applied in the Turkish DAM to solve its problems within a certain period of time	Used for a shorter period of time
57	Modeling spot price dependence in Australian electricity markets with applications to risk management	Katja Ignatieva and StefanTruck	2016	Archimedean, elliptical and copula mixture models applied on the Australian regional electricity markets suggesting that Student-t and mixture copula models are better during back testing. Non-linear methods	Variables like weather, electricity demand or transmission constraints need to be studied

S. No	Title	Author	Year	Findings	Gap
				better than GARCH models in case of multivariate analysis	
58	Asymmetric volatility in European day-ahead power markets: A comparative microeconomic analysis	Erkan Erdogdu	2016	EGARCH and TARCH models applied on 14 wholesale electricity markets in Europe suggesting positive leverage effect in Nordic countries, Ireland, and the UK after 2008 and negative leverage effect on countries like the Czech Republic, Russia, and Turkey	Reasons for price movements need to be studied
Theme 6: Forecasting					
59	A neural network-based estimator for electricity spot pricing with particular reference to weekend and public holidays	A.J. Wang and B. Ramsay	1998	Back propagation method applied to study the weekend and public holidays' effect on the prices of England and Wales in 1990 suggesting that holiday have more impact than weekdays on fluctuation in the prices	Bidding problems can be studied further with this model
60	Electricity price short term forecasting using artificial neural networks	B.R. Szkuta, L.A. Sanabria, T.S. Dillon	1999	Applied ANN (artificial neural network) on the Victoria electricity market suggesting it to be a good model	Other variables can also be incorporated for further study
61	Forecasting energy prices in a competitive market	Jeffrey Bastian, Jinxiang Zhu, Venkat Banunarayanan, and Rana Mukerji	1999	Predicted the prices of PJM electricity market suggesting market assessment and portfolio strategies method to be better	Other models can also be applied

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62	Electricity price forecasting in deregulated markets: A review and evaluation	Sanjeev Kumar Aggarwal, Lalit Mohan Saini, Ashwani Kumar	2000	A review of the forecasting techniques applied in the global electricity market	Better tools can be applied with a period of time
63	Prediction of system marginal price by wavelet transform and neural network.	Changil Kim, InKeun Yu, and Y.H. Song	2000	Predicted electricity prices of the UK Power pool suggesting that wavelet transform model is a good model	Other models can also be applied
64	A comparison of two techniques for next-day electricity price forecasting	Alicia Troncoso Lora, Jesus Riquelme Santos, Jose Riquelme Santos, Antonio Gomez Exposito, and Jose Luıs Martınez Ramos	2002	Models were applied on the hourly prices of the Spanish electricity market from January 2001 to August 2001 such as k weighted nearest neighbours (kWNN) and a dynamic regression (DR)	Application of risk mitigation techniques possible
65	Evaluation of support vector machine-based forecasting tool in electricity price forecasting for Australian national electricity market participants	D.C. Sansom, T. Downs, and T.K. Saha	2003	Applied SVM(support vector machines) and NN(neural network) to predict the electricity prices of the Australian national electricity market from September to December 1998 suggesting both to be accurate models	Application of risk mitigation techniques possible
66	ARIMA models to predict next-day electricity prices	Javier Contreras, Rosario Espinola, Francisco J. Nogales, and Antonio J. Conejo	2003	ARIMA (auto-regressive integrated moving average) model applied on the electricity prices of the Spanish and Californian markets suggesting different results for different markets	ANN (artificial neural network) models can be applied for future study
67	Energy clearing price prediction	Li Zhang, Peter B. Luh, and	2003	Applied cascaded neural network on the	Extended versions with

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	and confidence interval estimation with cascaded neural network	Krishnan Kasiviswanathan		ISO New England electricity market suggesting the results are fine	multilayer perception and radial basis function can be applied
68	Periodic heteroskedastic Reg ARFIMA models for daily electricity spot prices	M. Angeles Carnero, Siem Jan Koopman, and Marius Ooms	2003	Four European electricity markets were studied like the APX in the Netherlands, the EEX in Germany, the Powernext in France, and the Nord Pool in Norway suggesting seasonal Reg ARIMA model the best fit model to be applied in APX, EEX, and Powernext and a periodic long memory model for Nord Pool	Joint modelling can be done among these markets
69	A regime switching long memory model for electricity prices	Niels Haldrup and Morten.O. Nielsen	2004	Regime switching model applied in the Nordic electricity market suggesting that the model is empirically correct	Multivariate analysis can be done for better study for longer periods
70	Forecasting electricity spot-prices using linear univariate time-series models	Jesus Crespo Cuaresma, Jaroslava Hlouskova, Stephan Kossmeier, Michael Obersteiner	2004	Hourly electricity prices of Leipzig Power Exchange was studied using ARIMA model suggesting it to be a good model	Use of better models can be done
71	Short-term electricity price modeling and forecasting using wavelets and multivariate time series	Haiteng Xu and Tak Niimura	2004	Applied multivariate analysis on PJM electricity market to predict the prices suggesting results are satisfactory	Other variants of wavelets can also be applied

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72	Improving market clearing price prediction by using a committee machine of neural networks	Jau-Jia Guo and Peter B. Luh	2004	ANN using multiple layers is applied on the New England market suggesting better results	Other models can also be applied
73	Price forecasting using integrated approach	Z. Hu, Y. Yu, Z. Wang, W. Sun, D. Gan, and Z. Han	2004	Applied BP model in the Zhejiang electricity market suggesting it to be a good model	Other models can also be applied
74	Periodic Seasonal Reg-ARFIMA-GARCH models for daily electricity spot prices	Siem Jan Koopman, Marius Ooms, and M. Angeles Carnero	2005	Applied periodic seasonal Reg-ARFIMA-GARCH models on the daily spot prices of four European electricity markets suggesting that among them the model was accurate for Nord pool	Longer periods, higher frequency, and multivariate analysis needs to be conducted
75	An empirical examination of restructured electricity prices	Christopher R. Knittel and Michael R. Roberts	2005	Applied various forecasting models on the prices of California electricity market from 1st April 1998 to 30th August 2000 incorporating seasonal effect factors suggesting that peculiar nature of electricity make the application of statistical model a bit impractical to apply in reality	Only seasonality considered, other factors are yet to be incorporated
76	Pricing in electricity markets: A mean reverting jump diffusion model	Alvaro Cartea and Marcelo G. Figueroa	2005	Mean reverting jump diffusion model applied on the spot and forward prices of England and Wales electricity market	Different models can be applied

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	with seasonality			suggesting that the model is not accurate	
77	Forecasting electricity prices for a day-ahead pool-based electric energy market	Antonio J. Conejoa, Javier Contreras, Rosa Espınola, Miguel A. Plazas	2005	Applied models on the electricity prices of PJM Interconnection of the year 2002 suggesting that ARIMA models are considered to be the best on the data set	Combinations of two models can be applied for future study
78	A GARCH forecasting model to predict day-ahead electricity prices	Reinaldo C. Garcia, Javier Contreras, Marco van Akkeren, and Joao Batista C. Garcia	2005	GARCH model applied on the Spain and California electricity-markets are discussed	Factors like calendar effect and other exogenous variables (water storage, weather, etc.) could also be incorporated in the data
79	Neural network-based market clearing price prediction and confidence interval estimation with an improved extended Kalman filter method	Li Zhang and Peter B. Luh	2005	DEKF-UD method is applied on the prices of ISO New England's electricity market suggesting it to be a good model	Other models using congestion management can also be applied
80	A general method for electricity market price spike analysis	Jun Hua Zhao, Zhao Yang Dong, Xue Li, and Kit Po Wong	2005	Studied the Australian electricity market by applying support vector machine and probability classifier suggesting it to be a good method	Other models can also be applied
81	Stable modeling of different European power markets	Christian Mugele, Svetlozar T. Rachev and Stefan Trück	2005	ARMA (auto-regressive moving average)/ GARCH, GARCH – M(GARCH-in-mean) model and stable	Models like jump diffusion or regime switching models can be

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				Paretian distribution time series models are applied on the German, Nordic, and Polish power markets to conduct forecasting giving varying results in each model	applied on the data series
82	An empirical examination of restructured electricity prices	Christopher R. Knittel, Michael R. Roberts	2005	Forecasting performance and leverage effect of the Northern California market is studied from 1st April 1998 to 30th August 2000 applying various methods suggesting the data is having inverse leverage effect and suggesting the incorporation of various seasonal features would improve the results	All the factors yet not considered
83	Electricity price forecasting with confidence-interval estimation through an extended ARIMA approach	M. Zhou, Z. Yan, Y.X. Ni, G. Li, and Y. Nie	2006	ARIMA model with error correction applied California power market suggesting it to be a good model	Other models on locational marginal price can be applied keeping congestion in mind
84	Spot and derivative pricing in the EEX power market	Michael Bierbrauer , Christian Menn , Svetlozar T. Rachev , Stefan Truck	2007	Applied various models on the German electricity market prices from 1st October 2000 to 30th September 2003 suggesting regime switching models to be better than the rest	Can be applied in other European markets

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85	An artificial neural network approach for short-term electricity prices forecasting	J.P.S. Catalao, S.J.P.S. Mariano, V.M.F. Mendes, and L.A.F.M Ferreira	2007	A three- layered FFNN(feedforward neural network) method is better than the ARIMA method when applied on the mainland Spanish market	Other models can also be applied
86	Short-term electricity prices forecasting in a competitive market: A neural network approach	J.P.S. Catalao, S.J.P.S. Mariano, V.M.F. Mendes, and L.A.F.M Ferreira	2007	A three- layered FFNN method is better than the ARIMA method when applied on the mainland Spanish and California market suggesting it to be an accurate model	Other models can also be applied
87	Next-day electricity-price forecasting using a hybrid network	S. Fan, C.Mao, and L. Chen.	2007	SVM was applied on a New England electricity market suggesting the accuracy of model	More market factors and long term data needs to be taken
88	Data mining of electricity price forecasting with regression tree and normalized radial basis function network	Hiroyuki Mori and Akira Awata	2007	Applied normalized RBFN(radial basis function network) method on the prices of ISO New England suggesting it to be a good model	Other models can also be applied
89	Reliability of ARMA and GARCH models of electricity spot market prices	Piotr Ptak, Matylda Jablonska, Dominique Habimana, and Tuomo Kauranne	2008	ARMA- GARCH forecast models applied validated by MCMC analysis on the electricity spot market prices of the Nordic Nord Pool and the US NE Pool giving ambiguous results	Reversible Jump MCMC model can be applied on the data to get better results
90	Forecasting electricity prices: The impact of fundamentals	Nektaria V. Karakatsani, Derek W. Bunn	2008	Price forecasts with a new rule for regime prediction, which incorporates	GARCH not applied

S. No	Title	Author	Year	Findings	Gap
	and time-varying coefficients			information on expected market fundamentals, were more accurate than Markov-predicted probabilities, which rarely indicated a spiky regime	
91	Short term forecasting of electricity prices for MISO (Midwest Independent System Operator) hubs: Evidence from ARIMA-EGARCH models	Nicholas Bowden and James E. Payne	2008	ARIMA, ARIMA-EGARCH, and ARIMA-EGARCH-M applied on the hourly electricity prices of the MISO suggesting ARIMA-EGARCH-M to be a better model	Usage of other tools
92	Volatility forecasting I: GARCH Models	Rob Reider	2009	Study of various GARCH models and suggestions to choose better models	Out of sample data can be studied further
93	Electricity spot price modelling with a view towards extreme spike risk	Claudia Kluppelberg, Thilo Meyer-Brandis, and Andrea Schmidts	2010	Sums of Levy-driven Ornstein–Uhlenbeck method is applied on EEX electricity spot price data and later EEX Phelix (physical electricity index) Base electricity price index suggesting it to be a good method despite of many drawbacks	Other models can also be applied
94	Electricity price forecasting using enhanced probability neural network	Whei Min Lin, Hong Jey Gow, and Ming Tang Tsai	2010	Enhanced probability neural network (EPNN) and PNN (Probability neural network) applied on PJM market suggesting EPNN to be a better forecasting model	Other models can also be applied

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95	Mid-term electricity market clearing price forecasting: A hybrid LS-SVM (Least squares support vector machine) and ARMAX approach	Xing Yan and Nurul A. Chowdhury	2013	Applied the combination of LS-SVM and auto-regressive moving average with external input (ARMAX) model on the electricity prices of PJM market from January 2009 to December 2009 to conduct medium term forecasting suggesting it to be an accurate model	Peak prices can be considered for future study
96	Day-ahead electricity price forecasting using wavelet transform combined with ARIMA and GARCH models.	Zhongfu Tan, Jinliang Zhang, Jianhui Wang, Jun Xu	2010	Applied a combination of ARIMA, GARCH, and wavelet theorem method on the Spanish and the PJM electricity market suggesting the method to be accurate	Other models can also be applied
97	Electricity demand and spot price forecasting using evolutionary computation combined with chaotic nonlinear dynamic model	C. Unsihuay-Vila, A.C. Zambroni de Souza, J.W. Marangon-Lima, and P.P. Balestrassi	2009	Used a hybrid approach in comparison with the ANN and ARIMA methods to predict electricity prices of New England, Alberta, and Spain suggesting it to be a better model than the rest	Other models can also be applied
98	Electricity price forecasting – ARIMA model approach	Tina Jakasa , Ivan Androcec, Petar Sprcic	2011	ARIMA model applied on the weekday and weekend prices of the EPEX(European Power Exchange) suggesting it to be a good model	Other methods can be applied

S. No	Title	Author	Year	Findings	Gap
99	A new prediction strategy for price spike forecasting of day-ahead electricity markets	Nima Amjady and Farshid Keynia	2011	Applied probabilistic neural network (PNN) and hybrid neuro-evolutionary system (HNES) method on the PJM (Pennsylvania–New Jersey–Maryland) electricity market suggesting it to be an accurate model	Medium term and extreme movements can be studied in future
100	Price forecasting of day-ahead electricity markets using a hybrid forecast method	M. Shafie Khah, M. Parsa Moghaddam, and M.K. Sheikh El Eslami	2011	This hybrid method based on wavelet transform, ARIMA models and RBFN is suggested to be the best model when applied on the electricity prices of mainland Spain	Other models can also be applied
101	Modeling and forecasting day-ahead hourly electricity prices: a review	G.P. Girish	2012	A review of the forecasting techniques applied in the global electricity market is done	A direction for future researchers is given
102	A mixed integer linear programming model of a zonal electricity market with a dominant producer	Maria Teresa Vespucci, Mario Innorta, and Guido Cervigni	2012	A mixed linear programming model applied on the Italian market to advocate bidding strategies to the electricity producers suggesting it to be a good model	Model to forecast prices of the Italian market can be proposed
103	Forecasting Nord Pool day-ahead prices with an auto-regressive model	Tarjei Kristiansen	2012	A regression model applied on the Nord Pool hourly prices from 1st January 2004 to 31st December 2006 along with Nordic demand and Danish wind power as variables giving good results	Other models can also be applied

S. No	Title	Author	Year	Findings	Gap
104	Electricity price forecasting with extreme learning machine and bootstrapping	Xia Chen, Zhao Yang Dong, Ke Meng, Yan Xu, Kit Po Wong, and H. W. Ngan	2012	ELM-Bootstrap MCPs forecasting method applied on the Australian market suggesting it to be a good model	Other models can also be applied
105	Applying ARMA–GARCH approaches to forecasting short-term electricity prices	Heping Liu, Jing Shi	2013	Various GARCH models in combination with ARMA was applied on the New England electricity prices from 1st January 2008 to 28th February 2010 suggesting ARMA–GARCH-M, ARMA–SGARCH-M, and ARMA–GJRGARCH-M models which are effective for forecasting on the data set	Other variables such as weather variables and holidays can be incorporated for future work
106	Price forecasting in the day-ahead energy market by an iterative method with separate normal price and price spike frameworks	Sergey Voronin and Jarmo Partanen	2013	Mixture of wavelet transform, linear ARIMA, and non-linear neural network models are applied on the Finnish Nord Pool spot day-ahead energy market suggesting it to be good model	The sensitivity analysis of energy costs to the price forecast needs to be studied further
107	Spot electricity price modeling and forecasting	G.P. Girish	2013	A review of all the forecasting techniques that can be applied in the Indian electricity market	Forecasting exchange traded electricity prices to be studied further
108	Optimum long-term electricity price forecasting in noisy and complex environments	A. Azadeh, M. Moghaddam, M. Mahdi, and S. H. Seyedmahmoudi	2013	Models applied on the electricity prices of Iran from 1972 to 2007 suggesting fuzzy linear regression (FLR), and conventional linear	Other models can also be applied

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				regression (CLR) models to outperform the ANN model	
109	Electricity price forecasting: A review of the state-of-the-art with a look into the future	Rafał Weron	2014	Provided review of the various models applied on the global electricity markets suggesting its strengths and weaknesses	The techniques can be applied pn the global electricity markets
110	Modeling and forecasting of day-ahead electricity price in Indian energy exchange – evidence from MSARIMA-EGARCH model	Sajal Ghosh and Kakali Kanjilal	2014	Applied MSARIMA (multiple seasonal ARIMA) and MSARIMA-EGARCH models on the Indian Energy Exchange hourly prices from 1 September 2008 to 30 September 2008 suggesting the latter method to be better than the other in terms of forecasting	Other models from GARCH family can be studied on the same data set
111	Electricity price forecasting model - defining the need and approach for the Indian market	Jasdev Singh Soni	2014	A review of the electricity forecasting methods and need for forecasting is mentioned in the paper	Various models can be applied for forecasting
112	A hybrid ARFIMA and neural network model for electricity price prediction	Najeh Chaabane	2014	Combination of ARFIMA and ANN models applied on the Nord Pool electricity prices from 1st October 2012 to 28th November 2012 suggesting it to be an accurate model	Other models can also be applied
113	Spot electricity price forecasting in Indian	G.P. Girish	2015	Applied combination of ARIMA with variety of GARCH	Spillovers and multivariate analysis are a

S. No	Title	Author	Year	Findings	Gap
	electricity market using auto-regressive-GARCH models			models on the Indian electricity market from 1st October 2010 to 30 September 2013. The study suggests that ARIMA-PARCH (1, 1) model for northern, eastern, and north-eastern regions whereas ARIMA-GARCH (1, 1) model for western region and ARIMA-EGARCH model for southern region are accurate	future scope of study
114	Artificial neural networks for spot electricity price forecasting: a review	S. Vijayalakshmi and G. P. Girish	2015	A review of all the ANN models across the globe was done	ANN models can be applied for future study in Indian electricity
115	Price forecast valuation for the NYISO(New York Independent System Operators) electricity market	Dawit Zerom	2015	Application of ZK1 forecast in the NYISO market suggesting that better forecast does not guarantee rising profits.	The new forecast-evaluation framework can be adapted to work with other electricity markets, generators, fuel prices, and forecasting models
116	Modeling electricity spot prices: combining mean reversion, spikes, and stochastic volatility	Klaus Mayer, Thomas Schmid and Florian Weber	2015	Application of a simple Ornstein–Uhlenbeck model over a jump–diffusion model, proposed by Cartea and Figueroa (2005), constant volatility, and EGARCH	Better forecasting with longer series data set

S. No	Title	Author	Year	Findings	Gap
				volatility on the four electricity markets: France, Germany, Scandinavia, and Great Britain from time series from 1 January 2004 to 31 December 2009 for option pricing. EGARCH better among all	
117	Probabilistic forecasting of hourly electricity prices in the medium-term using spatial interpolation techniques	Antonio Bello, Javier Reneses, Antonio Munoz, and Andres Delgadillo	2015	Models applied on the Spanish market to conduct medium term forecasting from 1st August 2012 to 31st October 2013 creating various scenarios and then applying the model suggesting it to be a good model	Usage of sophisticated tools can be done
118	Empirical analysis of developments in the day -ahead electricity markets in India	Pankaj Sinha and Kritika Mathur	2016	Six variations of ARMA GARCH models are applied on the 15- minute W2 bid area prices of IEX from 1st April 2010 to 31st March 2014 suggesting that the volatility has declined in this area with the introduction of 15-minute blocks	More empirical studies can be conducted in this particular area
119	A comparison of different univariate forecasting models for spot electricity price in India	G. P. Girish and Aviral Kumar Tiwari	2016	ARFIMA model, auto-ARIMA model, Taylor's double seasonal Holt-Winter's model, exponential smoothing state space model, and theta forecast applied on the electricity price of Indian electricity	Other models like APARCH, CGARCH, etc. can be applied for future research

S. No	Title	Author	Year	Findings	Gap
				market from 1st January 2010 to 31st December 2015 suggesting ARIMA, Nile theta, and ETS (error, trend, seasonality) model to be the best among all	
120	A non-parametric structural hybrid modeling approach for electricity prices	S. Moazeni, M. Coulon, I. Arciniegas Rueda, B. Song, and W.B. Powell	2016	The model is applied on the the spot and forward electricity prices of the PS/ PSEG (Public Service Electric and Gas Company) zone in the PJM market suggesting it to be a good market	New models can be applied
121	Day-ahead electricity price forecasting via the application of artificial neural network based models	Ioannis P. Panapakidis and Athanasios S. Dagoumas	2016	Applied ANN on the Italian market suggesting it to be an efficient model	New models can be applied
122	Forecasting day-ahead price spikes for the Ontario electricity market	Harmanjot Singh Sandhu, Liping Fang, Ling Guan	2016	A base neural network applied on the Ontario electricity market for 30 days suggesting it to be a good model	Future forecasting on the data set can also be done
123	Modeling and forecasting multivariate electricity price spikes	Hans Manner, Dennis Turk, and Michael Eichler	2016	A dynamic copula based multivariate discrete choice model (DCMDC) was applied on the four markets of Australian hourly electricity spot prices from 1st January 2008 to 31st December 2012 suggesting it to be a good model	New tools on an impulse response analysis can be applied in future to improve the utility of the model

S. No	Title	Author	Year	Findings	Gap
124	Prediction of extreme price occurrences in the German day-ahead electricity market	Lars Ivar Hagsfors, Hilde Horthe Kamperud, Florentina Paraschiv, Marcel Prokopczuk, Alma Sator, and Sjur Westgaard	2016	The models are applied on the PHELIX (physical electricity index) hourly prices in the German electricity market from 4th January 2010 to 31st May 2014 suggesting that extremely high and negative prices have different drivers and that wind power is vital for the negative price occurrences	More advanced volatility model e.g. GARCH can be applied
125	Modeling electricity future prices using seasonal path-dependent volatility	Viviana Fanelli, Lucia Maddalena, Silvana Musti	2016	HJM(Heath–Jarrow–Morton) model applied on the future prices of German electricity market on the basis of which call options are studied and estimated to give accurate results	More risk mitigation techniques can be applied
126	Volatility forecast based on the hybrid artificial neural network and GARCH-type models	Xunfa Lua, Danfeng Quea, and Guangxi Caoa	2016	Combination of variants of GARCH with ANN model is applied on the Chinese energy index in Shanghai Stock Exchange from 31st December 2013 to 10th March 2016. suggesting that EGARCH-ANN to be an accurate model	Other models can also be applied
127	Day- ahead price forecasting in deregulated electricity market using artificial neural network	Ms. Kanchan K. Nargale and Mrs. S. B. Patil	2016	Application of feedforward method for a period of 5 days in IEX and PXIL from 13th April 2010 to 18th April 2010 suggesting it to be an accurate model	Other models can also be applied on the market

S. No	Title	Author	Year	Findings	Gap
128	Electricity price forecasting by a hybrid model, combining wavelet transform, ARMA, and kernel-based extreme learning machine methods	Zhang Yang, Li Ce, and Li Lian	2017	Combination of wavelet transform, the Kernel extreme learning machine (KELM), and ARMA model applied on the electricity prices of the Pennsylvania-New Jersey-Maryland (PJM), Australian and Spanish markets suggesting it to be good model	In the future, other factors such as load and weather can be taken into consideration
129	Electricity price modeling with stochastic time change	Svetlana Borovkova, Maren Diane Schmeck	2017	Hybrid model is applied on the EEX power prices incorporating seasonal features, suggesting it to be a good model for the year 2009	Other factors of electricity can be incorporated
130	Forecasting day-ahead electricity prices using a new integrated model	Jin Liang Zhang, Yue-Jun Zhang, De Zhi Lie, Zhong Fu Tan, and Jian-Fei Ji	2019	A new integrated model on Improved empirical mode decomposition (IEMD), ARMAX, EGARCH and adaptive network-based fuzzy inference system (ANFIS) is applied on the prices of Spanish and Australian electricity markets from 1st November 2017 to 30th November 2017, suggesting it to be an accurate model	Better forecasting tools can be applied

2.4 RESEARCH GAPS

The process of research gap identification follows a funnel down approach in which I have first studied the global electricity market, then the Indian electricity market to identify the area of research. It was found that the short-term Indian electricity market is still a niche market and poses many risks (price risk being a major risk). Further, the determinants of the electricity prices were studied, where it was found that volatility in the electricity market is a huge problem and there is a smaller number of efficient tools to measure the intensity of volatility and to predict it. Hence this research focusses on finding the proper tool to measure volatility and predict the prices.

Gaps from literature	**Reference**
1.) Limited application of volatility and forecasting models in the Indian Energy Exchange Day-ahead Market (especially in the bid areas)	Girish, 2012 Girish, 2015 Ghosh, 2014 Soni, 2014
2.) Models from the GARCH family are sparsely applied in the volatility study of the Indian electricity market, hence comparison between models of GARCH needs to be done for accurate modeling	Anamika and Kumar, 2016 Girish and Tiwari, 2016 Nargale and Patil, 2016 Sinha and Mathur, 2016
3.) An only univariate study was done that too on the usage of limited number of GARCH methods: Validation by ANN methods is required in each of the bid areas of the Indian Electricity Exchange-trade market	

2.5 CHAPTER SUMMARY

In order to identify the research problem, objectives, business problem, research question and its motivation, an intensive literature review (both academic as well as corporate reports) were conducted. The literature review was segregated into six themes of the power trading market which included the study of the global electricity market, Indian electricity market, risks involved in electricity trading business, determinants creating price risk, modeling volatility, and applying forecasting tools on the electricity market. Study of all the themes has led to the identification of the gaps thereby leading to the smooth application of the research methodology, mentioned in the next chapter.

CHAPTER 3
RESEARCH METHODOLOGY

3.0 CHAPTER OVERVIEW

The study and application of volatility and forecasting models in the Indian Electricity Exchange market are still at an embryonic stage. This study investigates various methods or tools which will help the power market stakeholders to make wise decisions regarding power purchase cost and investments. This research aims to cater to three main objectives such as (a) To study the volatility of the price in the day-ahead market since its inception (b) To do a comparative study of the two well-known volatility models, sparsely applied in the Indian electricity day-ahead market (c) To provide an accurate forecasting technique to be applied in the day-ahead market followed by forecasting the prices for the next 25 days.

This chapter outlines the modus operandi in which the research questions are answered in line with the research problem. The current study employs quantitative methods (using statistical tools) applied to the data collected from secondary sources (from the India Energy Exchange site). The reason to conduct a study in the Indian electricity day -ahead market has already been justified in Chapter 1 with gap identification in Chapter 2, hence these will not be covered here. Also, the directions for the future scope of research will be mentioned in Chapter 5 and will not be discussed here.

3.1 RESEARCH PROCESS

After conducting an intense study of the literature, which was divided into six themes and a funnel down approach for gap identification, this research aims at following a quantitative approach to meet the below-mentioned research questions:

Research Question 1: What is the intensity of volatility in the Indian Electricity DAM?

Research Question 2: Is measuring the intensity of volatility the only measure of analysis?

Research Question 3: What could be the probable forecasting techniques that can be applied in the bid areas of DAM?

Each research question leads to the identification of the three major objectives around which this research will revolve.

The research objective of the study are as follows:

- To study the volatility of the price in the day-ahead market since its inception
- To do a comparative study of the two well-known volatility models, sparsely applied in the Indian electricity DAM
- To provide an accurate forecasting technique to be applied in the DAM.

To meet each of the objectives mentioned above, a quantitative approach was adopted, and each objective was met by following a clear process mentioned below and briefly elucidated in Figure 3.1.

- For RO1: An econometric model (GARCH [generalized auto-regression conditional heteroscedasticity] model, derived to be best among the literature study adopted by the researcher) was applied to investigate volatility.
- For RO2: Another suitable model from the GARCH family was adopted to check the leverage effect in the data as well to check the best fit model.
- For RO3: Applied econometric models such as GARCH, ARIMA [auto-regressive integrated moving average], and ANN [artificial neural network] to forecast the electricity prices, did a comparative study among the three

well-known models according to the literature, and concluded with the best fit model.

The detailed process to meet each objective will be explained later in this chapter after the data collection.

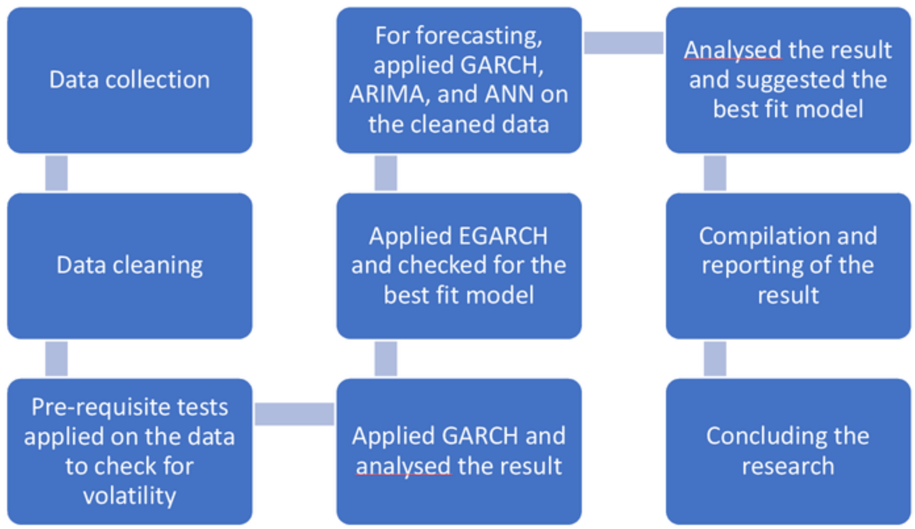

Figure 3.1: Research process for the current research.

In the above diagram, the best fit model for GARCH (generalized auto-regressive conditional heteroscedasticity), EGARCH(exponential GARCH), ARIMA(auto-regressive integrated moving average), and ANN(artificial neural networks) depends on the lowest values of AIC (Akaike Information criterion), BIC (Bayesian information criterion), SC (Schwarz criterion), and RMSE (root mean square error).

3.2 DATA COLLECTION

To achieve the objectives, the current research consists of study through secondary sources wherein firstly many research papers and scholarly articles were studied to get the overview of the global and the Indian electricity market and to identify the underlying problems in the electricity traded market. Out of the plethora of papers and articles, to get a stronger and more unbiased view of the theories and the concept, all the scholarly articles and books were sorted out and arranged in a chronological manner which have ultimately led to the identification of the gap and the area in which research can be conducted.

Following are some of the major organizations whose reports and publications have been referred.

- The IEX (Indian Energy Exchange)
- The PXIL (Power Exchange India Limited)
- Central Electricity Authority (CEA), Government of India
- Central Electricity Regulatory Commission (CERC)
- International Energy Agency
- Reports of Planning Commission of India
- Reports of the Distribution Companies
- Form IV of the Short-term Bilateral Electricity Traders
- Ministry of Power
- Scholarly articles/ journals

Through the above-mentioned sources, it was found that study of volatility and forecasting is still a grey area in Indian electricity day-ahead market. Hence this research focusses on the study of volatility and forecasting of the daily IEX's DAM prices of all the 13 bid areas (A1, A2, E1, E2, N1, N2, N3, S1, S2, S3, W1, W2, and W3) from 1st August 2008 to 31st August 2017. The spot price is defined as the "intersection of the total demand curve and the total supply curve, for a given particular hour, for each region of the electricity market" (Girish, 2014).

The details of the bid areas along with the observations taken has been illustrated in Table 3.1. The variation in the observations of the bid areas is due to non-availability of the data on certain dates, hence while cleaning the data, missing observations were not taken into consideration. It has also been observed that the data of E1 and E2, A1 and A2, N2 and N1, S2 and S3, and W1 and W2 are the same; hence the data of E1, A1, N1, N3, S1, S2, W1, and W3 was only considered for easier application of model and presentation of data.

Bid Area	Unit	Data start date	Data end date	Observations
A1	Rs/kWh	1st August 2008	31st August 2018	3312
E1	Rs/kWh	1st August 2008	31st August 2018	3312
N1	Rs/kWh	1st August 2008	31st August 2018	3312
N3	Rs/kWh	1st August 2008	31st August 2018	3294
S1	Rs/kWh	1st August 2008	31st August 2018	3312
S2	Rs/kWh	1st August 2008	31st August 2018	3143
W1	Rs/kWh	1st August 2008	31st August 2018	3312
W3	Rs/kWh	1st August 2008	31st August 2018	3312

Table 3.1: Details of the data used in this research.

The descriptive statistics of the data is elucidated in Table 3.2 below.

Bid area /Statistics	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
N1	3548.34	2925.23	15447.5	1016.2	1868.66	2.36	9.28
A1	3401.14	2809.52	13842.93	467.19	1788.95	2.29	8.89
E1	3357.65	2764.21	13842.93	467.19	1800.28	2.32	8.97
N3	3630.87	2974.95	15447.5	1016.2	1907.01	2.28	8.65
S1	4820.49	4271.69	17532.89	467.19	2315.31	1.28	5.1
S2	5131.74	4599.24	17532.89	467.19	2510.11	1.04	4.09
W1	3368.66	2779.75	13842.93	467.19	1789.38	2.35	9.11
W3	3294.25	2687.57	13842.93	467.19	1821.53	2.31	8.89

Table 3.2: Descriptive statistics for spot electricity prices.

From the table 3.2, it has been observed that the volatility in the southern region is highest from the year 2008 to 2017 as the standard deviation is at its peak in the southern region and lowermost in north- eastern region. The range of prices is highest in the southern region and lowest in the northern region. Skewness measures the asymmetry of a distribution. Since the data is positively skewed, it shows that the chance of prices going up in all the regions is comparatively higher than the mean rather than going down. The reason behind the prices going up is due to congestion in the transmission corridor. Kurtosis measures the extent to which observations cluster around a central point. Since the kurtosis for each bid area is more than 3, hence the data is leptokurtic i.e. it is dispersed away from the mean.

Stepwise research methodology to achieve each of the objectives is explained in the upcoming paragraphs.

3.3 TEST AND MODELS APPLIED

This portion of the chapter will throw light on the test and models used to meet each of the research objectives.

3.3.1 STUDY OF VOLATILITY - RESEARCH OBJECTIVE 1 AND 2

To conduct a study of volatility in the Indian electricity market, the following steps were involved:

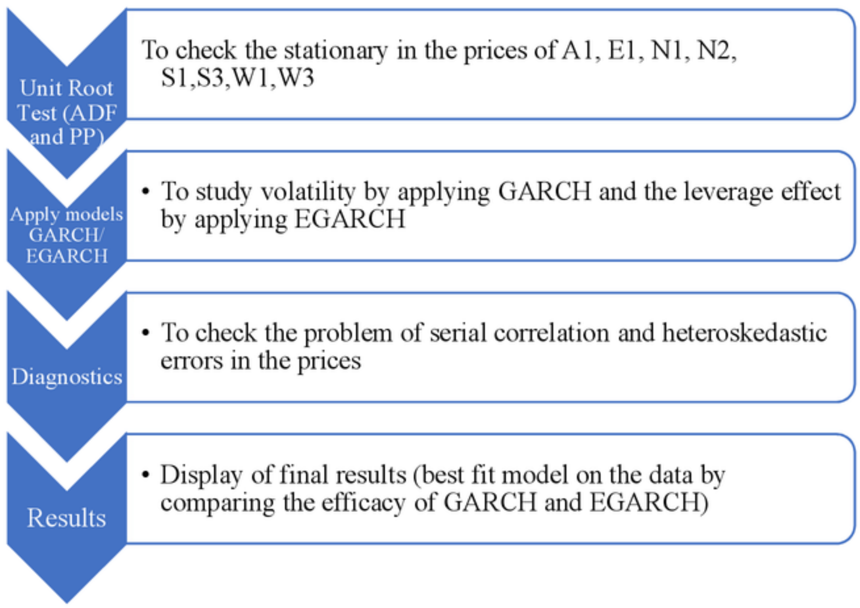

Figure 3.2:Detailed process to apply GARCH(1,1) and EGARCH(1,1).

3.3.1.1 UNIT ROOT TESTS

Unit root tests are conducted to check whether the data is stationary or not. If the series is stationary, then only we will proceed further with the other tests otherwise first level differentiating takes place.

Here in the series, we have applied two tests namely Augmented Dickey-Fuller (ADF) test formulated by D.A. Dickey and W.A. Fuller in 1979, and Phillips–Perron (PP) test developed by Phillips and Perron (Phillips and Perron, 1988).

It has been observed that the regular unit root tests such as ADF and PP give ambiguous results if the presence of structural breaks is ignored. Hence, it is important to run a structural break test to check whether mean reversion is there or not, which is an important step to run the GARCH (Generalized auto-regression conditional heteroskedasticity) model (Hiremath, 2014).

Considering this, the Zivot-Andrews sequential break test is applied. Zivot-Andrews structural break unit root test was proposed by E. Zivot and D.W.K. Andrews in the year 1992.

3.3.1.1.1 AUGMENTED DICKEY-FULLER (ADF) TEST

The primary work on testing for a unit root in time series was done by D.A. Dickey and W.A. Fuller in 1979. This test basically checks the null hypothesis that whether a time series y_t is integrated at order 1 i.e. I (1) against the alternative that it is I (0) if data follows autoregressive moving average (ARMA process) structure. The equation of the ADF test is as follows (Said and Dickey, 1984):

$$y_t = \beta' D_t + \emptyset y_{t-1} + \sum_{1=1} \Psi_j \Delta y_{t-j} + \varepsilon_t \qquad (3.1)$$

Where D_t = deterministic terms,

Δy_{t-j} = serial correlation

Value of p is set such that the error term ε_t is serially not correlated and is implicitly assumed to be homoscedastic.

3.3.1.1.2 PHILLIPS–PERRON (PP) TEST

A more comprehensive test for non- stationarity was developed by Phillips and Perron (Phillips and Perron, 1988). The tests are like ADF (Augmented Dickey-Fuller) tests, but they include an automatic correction to the DF (Dickey-Fuller) procedure to allow for auto-correlated residuals.

The test regression for the PP tests is

$$\Delta y_t = \beta\, 0D_t + \pi y_{t-1} + u_t \tag{3.2}$$

$$u_t \sim I(0)$$

The PP tests rectifies the presence of any serial correlation and heteroskedasticity in the errors u_t of the test regression by directly adjusting the test statistics $t\pi$=0 and $T\pi$

3.3.1.1.3 ZIVOT- ANDREWS (1992) SEQUENTIAL BREAK TEST

Zivot-Andrews have developed three models such as model A which studies the break in intercept only, model B which studies the break in trend only, and model C which studies the break in both intercept and trend.

According to Sen (2003) who has extended the work of Zivot-Andrews, using maximum F-statistic version of Model C is the most reliable among the three models. Hence the researcher has employed model C to check for stationarity and a structural break in the empirical analysis.

The equation of Model C is as follows:

$$\Delta P_t = \mu + \theta DU_t(\lambda) + \beta t + \mathrm{y}DT_t(\lambda) + \alpha p_{t-1} + \sum_{j=1}^{k} \phi_j \Delta p_{t-j} + \varepsilon_t \tag{3.3}$$

In the above equation, ΔPt is the first difference of the process P_t, DU_t is a dummy variable which captures shift in the intercept, and DT_t is another dummy that represents a shift in the trend occurring at time T_B. $\infty, \propto, \gamma, \theta, \beta, \mu$ *and* φs are constants, λ is location of a breakpoint, and ε_t is the shock. These dummy variables are defined as follows:

DU_t (λ) = | 1 if t > TB

|0 otherwise

DT_t (λ) = | 1 if t > TB

| 0 otherwise

Zivot-Andrews tests are used to test for a unit root with one-time structural break both in intercept and trend at any point in the given data. To determine the breakpoint and calculate the test statistics for a unit root, an ordinary least square regression is run with a break at break date TB, where TB varies from 1 to T-2. An extra regressor k is chosen followed by a sequential downward t-test on all lags for each increase in value as suggested by Campbell and Perron (1991).

3.3.1.1.4 APPLYING GARCH AND EGARCH

The researcher has applied GARCH(generalized auto-regressive conditional heteroskedasticity) (1, 1) model on the data set, which is a type of GARCH (p,q) model, where, (p,q) was introduced by Bollerslev in the year 1986 which included p lags of the conditional variance in the linear ARCH(q) (auto-regressive conditional heteroscedasticity) conditional variance equation introduced by Robert Engle (1982). The GARCH(1,1) is the most popular model in the empirical literature and is expressed as follows:

$$\sigma_t^2 = \omega + \alpha\eta_{t=1}^2 + \beta\sigma_{t=1}^2 \tag{3.4}$$

Where: α parameter represents a magnitude effect and β measures the persistence in conditional volatility regardless of any movements in the market.

The GARCH model checks the presence of long-term volatility, but it does not analyse the leverage effect. This is because the conditional variance is a function only of the squared market values and the magnitudes of its past values, hence the positive or negative effect is not captured. To calculate the asymmetric relationship, which is also known as a leverage effect i.e. how negative shocks or positive shocks cause more volatility at the same magnitude as there are various models that have been used to measure the asymmetry. EGARCH (exponential GARCH) model is one of the models which captures asymmetric responses of the time-varying variance to shocks and ensures that the variance is always positive. The model was formed by Nelson (1991).

$$log\,\sigma_t^2 = \omega + \sum_{i=1}^{q}(a_i\eta_{t=1} + y(|\eta_{t=1}| - E|\eta_{t=1}|) + \sum_{i=1}^{q}\log\sigma_{t=1}^2 \tag{3.5}$$

$$\text{And } \epsilon_t = \sigma_t \eta_t \tag{3.6}$$

This model is different from the GARCH model as it takes the log of the conditional variance. The equation states that the leverage effect is exponential, rather than quadratic and that the forecast of the conditional variance is guaranteed to be positive. The leverage effect can only be tested if $\gamma i < 0$ and the impact is asymmetric if γi is not equal to 0.

The EGARCH model focusses on the asymmetric function of past innovation shocks. γ is referred to as the magnitude of the persistence of variance. The nearer the magnitude approaches to unity, the greater would be the persistence of shocks towards volatility. α and β determine the future variance where α is the magnitude effect and if $\alpha > 0$, then log (α) would be positive when the magnitude of (σ -j) is larger than its expected value and vice versa. β represents asymmetric effect and if $\beta = 0$, then there is non-existence of asymmetric volatility. If $\beta < 0$ and is statistically significant, the volatility of the return shock is asymmetric, and the negative volatility impact is larger than the same magnitude of positive shocks. Thus, the negative β represents the persistence of the leverage effects (Raju, Sengar, Jayaraj and Kulshreshta, 2016).

The application of GARCH (1,1) and EGARCH (1,1) basically involves three steps. The first is to estimate the best fitting auto-regressive model through ARCH- LM (auto-regressive conditional heteroscedasticity-Lagrange Multiplier) test; secondly, to compute the auto-correlations of the error term and lastly, to test for significance and values of alpha and beta.

3.3.1.2 DIAGNOSTICS

3.3.1.2.1 VOLATILITY CLUSTERING

Volatility clustering (which was first observed by Mandelbrot in 1963) refers to a concept where large variations tend to be followed by large variations, either in a positive or a negative direction and small variations are bound to be followed by small variations. All of this leads to high volatility. GARCH (generalized auto-regressive conditional heteroscedasticity) is used to model volatility clustering and how fast the prices revert to its mean. If the daily observations are less than 1000 in number, then GARCH (1,1) will not give proper result. The researcher has applied auto-regressive conditional heteroscedasticity-Lagrange multiplier (ARCH- LM) test to check for heteroscedasticity.

Engle's (1982) ARCH-LM test is the standard approach to detect ARCH effects. If the p-value for any number of lags is above .05, then the ARCH process is an adequate fit with the presence of volatility clustering and the null hypothesis cannot be rejected.

3.3.1.2.2 AUTO-CORRELATION

The Ljung-Box Q test (Ljung and Box, 1978) is conducted to check for auto-correlation within the standard residuals of the GARCH model. This test was an extension of the Box-Pierce test. If GARCH is performing well in the given data set, then there should be no auto-correlation within the residuals. The null hypothesis of the Ljung-Box test is that the auto-correlation between the residuals for a set of lags k is equal to 0. If at least one auto-correlation for a set of lags k is greater than 0, then the test statistic indicates that the null hypothesis may be rejected.

If the p-value is less than or equal to 0.05 (your significance level) then the null hypothesis will be rejected stating that the GARCH model has not captured the auto-correlation.

3.3.1.2.3 PERSISTENCE

The persistence of a GARCH(generalized auto-regressive conditional hetroskedasticity) model checks how fast large volatilities decay after a shock. For the GARCH (1,1) model, to check the same, the sum of two parameters (alpha1 and beta1) are taken into consideration. The sum of alpha1 and beta1 should be less than 1. If the sum is greater than 1, then the predictions of volatility are explosive — which is kind of unbelievable. If the sum is equal to 1, then we have to apply higher models such as GARCH (2,1), IGARCH (integrated GARCH), or EGARCH (exponential GARCH).

Once the models have been applied then the lowest value of Akaike's (1974) information criterion (AIC), Schwarz's (1977) Bayesian information criterion (SBIC/ SIC), and the Hannan--Quinn (1979) criterion (HQIC) (Brooks, 2008) is checked. The model having the lowest values is the best fit model between the two.

Algebraically, these are expressed as:

$$AIC = \ln(\hat{\sigma}^2) + 2k/T \tag{3.7}$$

$$SBIC = \ln(\hat{\sigma}^2) + (k/T)\ln T \tag{3.8}$$

$$HQIC = \ln(\hat{\sigma}^2) + (2k/T)\ln(\ln(T)) \tag{3.9}$$

where $\hat{\sigma}^2$ is the residual variance

$k = p + q + 1$ is the total number of parameters estimated and

T is the sample size.

3.3.2 STUDY OF FORECASTING - RESEARCH OBJECTIVE 3

This paragraph focusses on the methodology used to conduct a study of forecasting. To study forecasting three models were employed namely:

1) GARCH (generalized auto regressive conditional heteroscedasticity) (1,1)
2) ARMA (auto-regressive moving average) (p,q)
3) NNAR (neural network auto-regression)

GARCH (1,1) has already been explained in the previous paragraphs, hence will not be explained again.

A stepwise approach to applying ARMA and neural network auto- regressive method of ANN(artificial neural network) is explained in the Figure 3.3 and 3.4. (Anbazhagan & Kumarappan, 2012)

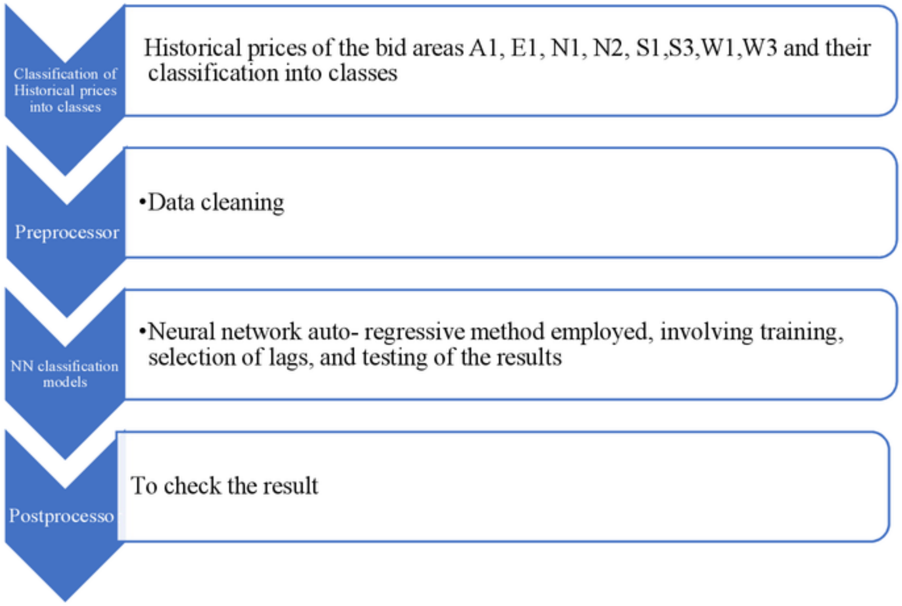

Figure 3.3: Detailed process of Neural Network Auto- Regressive method.

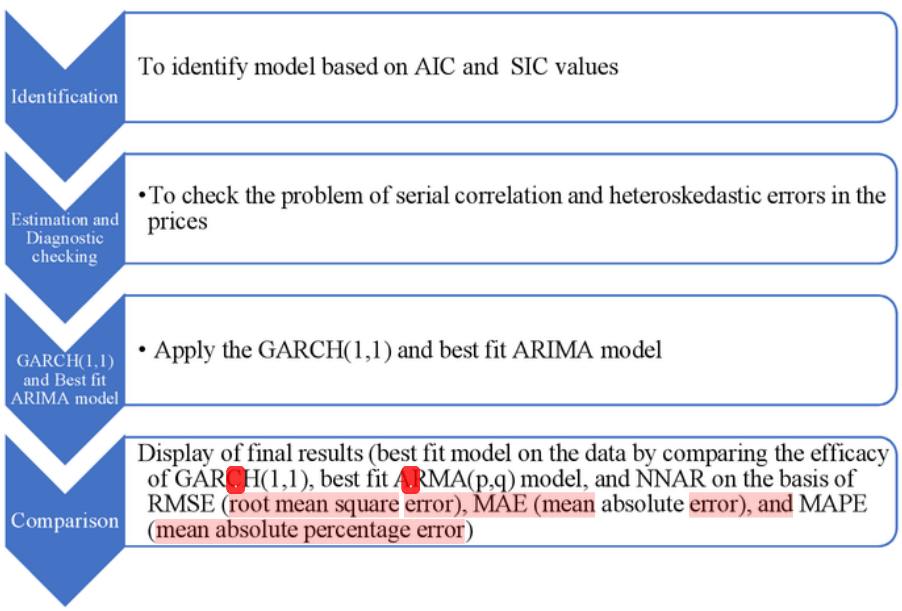

Figure 3.4: Detailed process to apply the GARCH (1,1) and the appropriate ARIMA model.

3.3.2.1 ARTIFICIAL NEURAL NETWORK

In the current research, the artificial neural network is used, which allows the modeling of complex non-linear relationships between the input variables and output variables. Among the various models used under the artificial neural network method, the researcher has applied the neural network auto-regression model (NNAR). Here, the lagged values of a time series are used as input to the model and the output are the predicted values of the time series. The benefit of using NNAR is that it does not impose any restriction on its parameters to ensure stationarity. The model NNAR (p, P, k) m proposed by Hyndman and Athanasopoulos (2018) is used due to the presence of seasonality in the electricity prices. Here the value of p states the value of ARIMA (auto-regressive integrated moving average), P states the presence of seasonality or not.; k states the number of neurons in the hidden layers. The structure of the NNAR (p, P,k)m is represented in the Figure 3.5.(Thoplan, 2014).

In the absence of any hidden layer, the NNAR (p, P, 0) m is equivalent to the SARIMA model denoted as an ARIMA(p,0,0) (P,0,0)m.

Faraway and Chatfield (1998) have suggested that a good neural network model should have a combination of both conventional modeling skills and time series. Here the researcher has taken m= 365 as the research involves the study of daily prices.

The NNAR model is a type of feedforward neural network model which includes a linear combination function and an activation function. The equation used to explain the linear combination function with neuron j is shown as:

$$net_j = \sum_i w_{ij} y_{ij} \tag{3.10}$$

The activation function is a sigmoid function defined as

$$f(y) = \frac{1}{1+e^{-y}} \tag{3.11}$$

The inputs of the neural networks are combined using a weighted linear function and the result of the combination is then modified into the non-linear sigmoid activation function, which becomes the input for the next layer. This process reduces the effect of extreme input values making the neural network a robust method for outliers. The weights taken in the beginning are the random values, which are further updated using the observed data. The network is trained several times using different random starting points, and the results are averaged (Hyndman and Athanasopoulos, 2018), to reduce the element of randomness in the predictions done by the method.

In the current data, the researcher has trained the model with data from 1 August 2008 to 31 December 2016 (90 % of the data) and tested with from 1 January 2017 to 31 August 2017. NNAR (30,1,16) [365] is applied using ARIMA (30,0,0), with 1 seasonality and 16 hidden layers, 365 states the number of days. Hence the researcher has used 31 – 16-1 model wherein 31 daily inputs with 16 hidden layers with 529 weight options are applied to get a single output.

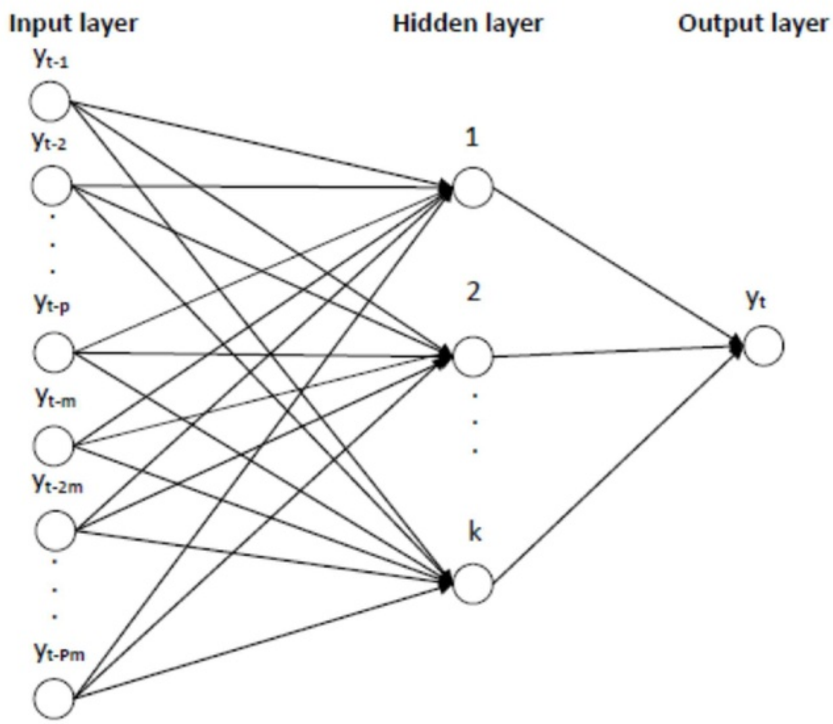

Figure 3.5:NNAR(p,P,k)m model: A diagrammatic view

3.3.2.2 ARMA OR AUTO-REGRESSIVE MOVING AVERAGE (BOX JENKINS MODEL (1976)

The generalized ARIMA (auto-regressive integrated moving average) (p, d, q) model coiled by Box and Jenkins in the year 1976 with p auto-regressive terms and q moving average terms and d degree of differentiating can be written in the form:

$$Y_t^{(d)} = c + \sum_{t=1}^{p} \phi_t^1 Y_{t-1} + \sum_{j=1}^{q} \theta_t^1 \epsilon_{t-j} \tag{3.12}$$

The ARIMA model is derived by combining auto-regressive terms, differentiating and moving average terms to create a more complete model. In general, p and q are not large because 1) the coefficients are likely to get small and not statistically significant with too many lag terms 2) the interpretations can get difficult with such large models and 3) with too many terms, we lose our predictive power due to overfitting. Overfitting is the case where we have too many parameters and end up modeling the random noise rather than the actual underlying relationships. Hence in this study, the researcher has taken maximum 3 values of p and 2 values of q with d = 0 as there is no unit root present in the data.

Now the appropriate AR (auto-regressive) and MA (moving average) terms are identified for each of the electricity market prices using the minimum AIC (Akaike information criterion) and SIC (Schwarz Bayesian information criterion), and the appropriate model for each bid area models among the various ARIMA models is selected.

Once the appropriate model is identified, the stationarity test is conducted, which in our case has already been done, while applying the GARCH (generalized auto-regressive conditional heteroskedasticity) model.

Since in our case d=0 hence ARMA (auto-regressive moving average) model is used, ARMA (p,q) models are time series models for stationary data—that is despite the data being stochastic, the probability distribution of our data remains constant.

Once the stationary test is conducive and there is no need for differentiating, the presence of auto-correlation is checked. In this study, the researcher has used Durbin- Watson test (Brookes, 2008) to test for first-order auto-correlation i.e. a relationship between an error and its immediately previous value. The test was coiled by J. Durbin and G.S. Watson in the year 1951.

The model has its null hypothesis and alternate hypothesis as:

H_0 = no first-order auto-correlation.

H_1 = first order correlation exists

(For a first-order correlation, the lag is one-time unit).

Assumptions of the test are as follows:

- That the errors are normally distributed with a mean of 0.
- The errors are stationary.

The formula used to calculate the test statistic is:

$$DW = \frac{\sum_{i=2}^{T}(\hat{u}_i - \hat{u}_{i-1})^2}{\sum_{i=2}^{T}\hat{u}_i{}^2} \qquad (3.13)$$

where μ_t are the residuals from the ARIMA model. As a thumb rule, the test statistic value ranging from 1.5 to 2.5 is considered to be normal and states there is no auto-correlation in the data (Brookes, 2008).

3.3.2.3 INTERPRETATION OF THE THREE MODELS

Once the three models i.e. GARCH (generalized auto-regressive conditional heteroscedasticity) (1,1), appropriate ARIMA (auto-regressive integrated moving average) model, and NNAR(neural network auto-regression) model has been applied then the accuracy of each is checked by comparing the actual values with the forecasted values of each model of the next 25 days. Also, to find out which one is the best model, the lowest values of RMSE (root mean square error), MAE (mean absolute error), and MAPE (mean absolute percentage error) is checked which can further be applied by the other researchers as well as the power market participants.

Each of the above-mentioned terms is defined as follows (Brookes, 2008):

3.3.2.3.1 ROOT MEAN SQUARE ERROR (RMSE)

This states by how much there is a standard deviation of the residuals from the mean

The formula used to define it is as follows (Barnston, 1992):

$$RMSE_{fo} = \left[\sum_{j=1}^{N}\left(Z_{fi} - Z_{0i}\right)^2/N\right]^{1/2} \tag{3.14}$$

Where:

- f = forecasts (expected values or unknown results)
- o = observed values (known results)
- Σ = summation ("add up")
- $(z_{fi} - Z_{oi})$ Sup>2 = differences, squared
- N = sample size

3.3.2.3.2 MEAN ABSOLUTE ERROR (MAE)

Mean absolute error (*MAE)* measures the average absolute forecast error and is defined as follows:

$$MAE = \frac{1}{T-(T_1-1)}\sum_{t=T_1}^{T}\left|\frac{|(y_{t+x}-f_{t,x})|}{y_{t+x}}\right| \tag{3.15}$$

- $T - (T_1\text{-}1)$ = the number of errors
- Σ = summation symbol (which means "add them all up")
- $|y_{t+x} - f_{t,x}|$ = the absolute errors

3.3.2.3.3 MEAN ABSOLUTE PERCENTAGE ERROR (MAPE)

The mean absolute percentage error (MAPE) is defined as follows:

$$MAPE = \frac{100}{T-(T_1-1)}\sum_{t=T_1}^{T}\frac{|(y_{t+x}-f_{t,x})}{y_{t+x}}| \tag{3.16}$$

Where:

- $\{y_{t+x}\}$is the actual observations time series
- $\{f_{t,x}\}$is is the estimated or forecasted time series
- $T - (T_1\text{-}1)$ is the number of non-missing data points

3.4 LIMITATIONS OF THE RESEARCH

The current study only includes application of the models on the data set from 1st August 2008 to 31st August 2017, although the Indian Energy Exchange have commenced its operations on 27th June 2008. The data of first two months has been excluded for the analysis as in the beginning it has been observed by the power market participants that the market exhibits unusual behavior (Bowden and Payne, 2008; Hadsell, Marathe & Shawky, 2004). Another limitation of the research was lack of availability of the data for some dates of the bid areas. Hence the missing data was eliminated for the successful application of the models which have further led to difference in the observations of the data set of some of the bid areas as mentioned before in this chapter.

The researcher has conducted a study using daily data of the Indian electricity day- ahead market series, which studies spike behavior with a duration of one day each, whereas electricity market in India have 15-minute time blocks, which are averaged to get the daily prices. Each day consisting of 96-time blocks in itself have strong variations which is yet to be explored.

Lag selection in each of the model was a problem for the researcher in order to get the best result, Hence the researcher has gone for the automatic selection by the software used (E-Views 10) to select the lag for each model.

While applying the NNAR(neural network auto-regression) model, the number of iterations and neurons in the hidden layer has been selected on the basis of ACF (auto-correlation function)plots in order to avoid the problem of overfitting.

3.5 CHAPTER SUMMARY

The chapter has thrown light on the methodology used to delve deeper into achieving the research objectives thereby catering to the research questions. The methodology adopted is described in an elaborative manner and is critically evaluated. A deeper analysis of the best-known models is done according to the literature studied by the researcher and the intricacies of each model is explained. The limitations of the current study have also been highlighted which will help other researchers and the power market participants to take wise decisions while applying the models on their data set.

The Indian electricity day- ahead market is an ideal data set which has been considered in this research as IEX is one of the leading electricity exchanges in India which offers a variety of products to the power market stakeholders which further has led to increase in efficiency and transparency in the power market. The Exchange offers electricity at low prices to its members, hence the Discoms, by doing a proper research in this area would optimize their power purchase cost thereby leading to maximization of profit.

CHAPTER 4
RESULTS AND ANALSIS

4.0 CHAPTER OVERVIEW

In chapter 2 & 3, the detailed literature review, gap identification, and the research methodology has been discussed which led to catering of the research questions. In this chapter, the data used in the research is analysed along with the detailed empirical result of the models applied for modeling and forecasting.

The chapter is divided into two parts. The first portion of the chapter gives the detailed result of the models used to conduct study of volatility of the Indian electricity day-ahead market prices and their comparison based on lowest Akaike information criterion AIC, Schwarz Bayesian information criterion (SBIC/ SIC), and the Hannan--Quinn criterion (HQIC) values (discussed in the previous chapter). The second part of the chapter throws light on the empirical result of the models used for forecasting the Indian electricity day-ahead market prices, their comparison based on the minimum values of RMSE (root mean square error), MAE(mean absolute error), and MAPE(mean absolute percentage error) followed by medium term forecasting of prices by each model for the next 25 days. The chapter further is concluded with the final remarks.

4.1 EMPIRICAL RESULTS— STUDY OF VOLATILITY OF THE INDIAN ELECTRICITY DAY- AHEAD PRICES

The following paragraphs discuss the empirical result of the two well-known models applied i.e. GARCH (generalized auto-regressive conditional heteroscedasticity) (1,1) and EGARCH (exponential generalized auto-regressive conditional heteroscedasticity) (1,1) used to study volatility in the Indian electricity day-ahead prices. Before applying the two models, the unit root test is conducted on the data set.

4.1.1 UNIT ROOT TEST

The researcher has applied 3-unit root methods to check whether the data is stationary or not (Each test has been explained in detail in the previous chapter). The result of each is explained as follows:

4.1.1.1 AUGMENTED DICKEY-FULLER TEST

	Augmented Dickey-Fuller Test			
	Test statistic	**1%**	**5%**	**p-value**
A1	-5.186	-3.43	-2.86	0.00
E1	-5.176	-3.43	-2.86	0.00
N1	-5.827	-3.43	-2.86	0.00
N3	-6.529	-3.43	-2.86	0.00
S1	-6.098	-3.43	-2.86	0.00
S2	-7.676	-3.43	-2.86	0.00
W1	-4.584	-3.43	-2.86	0.00
W3	-5.137	-3.43	-2.86	0.00

Table 4.1: ADF test statistics with intercept and trend.

ADF test works with the hypothesis of the series being H0: series contains a unit root and H1: series does not contain unit root. If the statistical value < 95% is of critical value, then the series is stationary and vice versa. In the above data set each of the eight-time series data, the ADF test statistic value is < critical value at 95% (Illustrated in Table 4.1) indicating that all the eight-time series are stationary. The same has been established by the p-value (<.05).

4.1.1.2 PHILLIP PERRON TEST

Phillip Perron Test

	Test statistic	1%	5%	p-value
A1	-7.89	-3.43	-2.86	0.00
E1	-7.62	-3.43	-2.86	0.00
N1	-7.93	-3.43	-2.86	0.00
N3	-8.49	-3.43	-2.86	0.00
S1	-8.06	-3.43	-2.86	0.00
S2	-9.63	-3.43	-2.86	0.00

	Test statistic	1%	5%	p-value
W1	-7.48	-3.43	-2.86	0.00
W3	-7.58	-3.43	-2.86	0.00

Table 4.2: PP Test statistics with intercept and trend.

In the case of the PP test, the t- statistic value is lesser than the critical value at 95% in each of the eight-time series data (Illustrated in Table 4.2). Also, the p-value for each is less than .05. Hence it indicates that the eight data series is stationary.

4.1.1.3 ZIVOT- ANDREWS TEST

As explained before the traditional unit root tests (such as ADF [Augmented Dickey-Fuller] and PP [Phillip Perron] as illustrated before) give vague results if the presence of structural breaks is not considered. Hence, it is important to conduct Zivot-Andrews sequential break (Model C) test which checks for the presence of the break in the data set. The results of the test are illustrated in Table 4.3.

	Zivot- Andrews test				
	Test statistic	1%	5%	10%	p-value
A1	-11.8517	-5.57	-5.08	-4.82	0.52
E1	-11.413	-5.57	-5.08	-4.82	0.57
N1	-12.46	-5.57	-5.08	-4.82	0.02
N3	-13.01	-5.57	-5.08	-4.82	0.02
S1	-9.1789	-5.57	-5.08	-4.82	0.00
S2	-8.833	-5.57	-5.08	-4.82	0.00
W1	-11.382	-5.57	-5.08	-4.82	0.53
W3	-11.42	-5.57	-5.08	-4.82	0.11

Table 4.3:Zivot-Andrews test statistic.

In the above table, the value of t- statistic for Model C which allows for both trend and intercept is lesser than the critical values at 1%, 5%, and 10 % stating that the data series is stationary with no presence of a structural break in the series.

Since the data series is stationary (mean and variance are constant over time), we can comfortably conduct GARCH (generalized auto-regressive conditional heteroscedasticity) (1,1) to check the volatility and presence of volatility clustering, the presence of persistence and auto-correlation, followed by application of EGARCH(exponential GARCH) (1,1) on the data set.

4.1.2 GARCH (1,1) MODEL

The result of the GARCH(generalized auto-regressive conditional heteroskedasticity) (1,1) model is as follows:

Bid Area/ Result	C	Alpha 1 (1)		Beta 1 (2)		Sum (1)+(2)
A1	0.008	0.681*	(0.00)	0.262*	(0.00)	0.943
E1	0.011	0.694*	(0.00)	0.208*	(0.00)	0.902
N1	0.007	0.767*	(0.00)	0.194*	(0.00)	0.961
N3	0.008	0.790*	(0.00)	0.161*	(0.00)	0.95
S1	0.011	0.837*	(0.00)	0.175*	(0.00)	1.012
S2	0.018	0.775*	(0.00)	0.183*	(0.00)	0.958
W1	0.006	0.736*	(0.00)	0.233*	(0.00)	0.969
W3	0.008	0.768*	(0.00)	0.190*	(0.00)	0.958

Notes: Figures in parenthesis are p-values. * - denote the significance at 5% level.

Table 4.4: Estimation of results of GARCH model for different bid areas of Indian electricity day-ahead market.

From the table above, it can be observed that for all the bid areas (except S1), the total of alpha1 and beta1 is lesser than 1, indicating the presence of mean reversion in the data. Since the sum is closer to 1, the reversion process will be quite slow. Whereas in the case of S1, the sum of both the parameters is equal to 1, stating we need to apply the EGARCH(exponential GARCH) model on the area.

From the above table, it can also be interpreted that the weightage for long term volatility based on long term rates is 5.7% (1-alpha1-beta1), 9.8%, 3.9%, 5.0%, -1.2%, 4.2%, 3.1%, and 4.1% for A1, E1, N1, N3, S1, S2, W1, and W3 respectively.

Also, the variance prediction model gives 68.1%, 69.4%, 76.7%, 79%, 83.7%, 77.5%,73.6%, and 76.8% weightage to the latest squared error term (deviance of returns from the mean) for A1, E1, N1, N3, S1, S2, W1, and W3 respectively.

26.2%, 20.8%, 19.4%, 16.1%, 17.5%, 18.3%, 23.3%, and 19.0 % weightage for A1, E1, N1, N3, S1, S2, W1, and W3 respectively is given to the variance based on the squares of previous time periods. It has also been observed that the p-values of alpha1 and beta1 is less than 0.05 stating that the values are significant.

4.1.2.1 WEIGHTED ARCH- LM TEST

To test the presence of volatility clustering (heteroscedasticity) in the data series, weighted ARCH –LM(auto-regressive conditional heteroscedasticity—Lagrange Multiplier) Test was conducted on 1 lag.

	A1	E1	N1	N3	S1	S2	W1	W3
WGT_RESID^2 (-1)	0.65	0.83	0.67	0.86	0.63	0.33	0.52	0.57

Source: Author's own analysis

Table 4.5: Weighted ARCH- LM test statistics for GARCH (1,1)

In the table above, it has been observed that the p-value for 1 lag is above .05, indicating that the ARCH process is an adequate fit and presence of volatility clustering is there, and we cannot reject the null hypothesis.

4.1.2.2 WEIGHTED LJUNG BOX TEST ON STANDARDIZED SQUARED RESIDUALS

Weighted Ljung Box Test on Standardized Squared Residuals was conducted on 6 lags to check the robustness of the model by investigating the presence of serial correlation in the residual and square of residual.

Lags	A1	E1	N1	N3	S1	S2	W1	W3
1	0.646	0.823	0.674	0.864	0.634	0.338	0.487	0.55
2	0.314	0.86	0.229	0.344	0.507	0.491	0.175	0.101
3	0.292	0.923	0.288	0.305	0.619	0.683	0.201	0.122
4	0.214	0.947	0.277	0.285	0.616	0.311	0.179	0.124
5	0.11	0.977	0.282	0.269	0.751	0.397	0.231	0.203
6	0.163	0.989	0.394	0.361	0.705	0.491	0.333	0.297

Table 4.6: Weighted Ljung Box Test on Standardized Squared Residuals.

Weighted Ljung Box Test on Standardized Squared Residuals was conducted on all the bid areas as shown in the table above. It has been observed that for the first 6 lags the residuals were not auto-correlated (as $p>.05$) for all the bid areas. Hence no serial correlation was present in the data series.

Overall, the diagnostic tests indicate that the GARCH (generalized auto-regressive conditional hetroskedasticity) model is correctly specified.

As explained in Chapter 3, the GARCH model only assumes analysing the magnitude of unexpected volatility helps in defining the result. Whereas not only the magnitude but also the direction (positive or negative) of the returns affects the volatility. Hence EGARCH (exponential GARCH) was applied to check the leverage effect on the Indian electricity DAM (day-ahead market) prices the results of which are as follows:

4.1.3 EGARCH (1,1) MODEL

The result of the EGARCH(exponential GARCH) (1,1) model is as follows:

Bid Area	**A1**	**E1**	**N1**	**N3**
C	7.886477	7.902667	7.957368	7.955587
Variance Equation				
C(2)	-1.24006* (0.00)	-1.4122* (0.00)	-1.62361* (0.00)	-1.64883* (0.00)
C(3) Alpha	0.913026* (0.00)	0.883321* (0.00)	1.14706* (0.00)	1.124* (0.00)
C(4) Gamma	0.110315* (0.00)	0.153094* (0.00)	0.117598* (0.00)	0.15155 (0.00)
C(5) Beta	0.836855* (0.00)	0.745189* (0.00)	0.778713* (0.00)	0.762793 (0.00)

Notes: Figures in parenthesis are p-values. * - denote the significance at 5% level.

Table 4.7: Estimation of results of EGARCH(1,1) model for bid areas (A1, E1, N1, and N3) of Indian electricity day-ahead market.

Bid Area	S1	S2	W1	W3
C	8.377377	8.505608	7.896829	7.864604
Variance Equation				
C(2)	-1.71405* (0.00)	-1.50368* (0.00)	-1.39681* (0.00)	-1.38883* (0.00)
C(3) Alpha	1.34979* (0.00)	1.142227* (0.00)	1.043488* (0.00)	1.024922* (0.00)
C(4) Gamma	-0.00597* (0.00)	-0.06169* (0.00)	0.097911* (0.00)	0.096765* (0.00)
C(5) Beta	0.761276* (0.00)	0.747803* (0.00)	0.82876* (0.00)	0.814206* (0.00)

Notes: Figures in parenthesis are p-values. * - denote the significance at 5% level.

Table 4.8: Estimation of results of EGARCH(1,1) model for bid areas (S2, E1, W1, and W3) of Indian electricity day-ahead market.

In Table 4.7 and 4.8, C is a constant and the equation is known as the mean equation. It shows that the probability is 0.00 that means that the model is a perfect fit and significant. C (2) is the constant of the variance equation, C (3) is the short-term shock or the ARCH (auto-regressive conditional hetroskedasticity) equation, C (4) is for the leverage effect, and C (5) is the long-term shock or the GARCH (generalized ARCH) equation.

Results for C (2), C (3), C (4), and C (5) are significant at 5% level of significance.

In S1 and S3, there is a negative leverage effect stating that the bad news such as transmission congestion and weather have more impact on the data set than good the news. Volatility is caused due to negative shocks in S1 and S2. Whereas in other bid areas, chances of volatility are less, and positive news has more impact than negative news. Positive C5 values in all the bid areas state that the past variances have an impact on the present data i.e. study of historical prices play an important role in determining the future prices.

4.1.3.1 WEIGHTED ARCH- LM TEST

To test the presence of volatility clustering (heteroscedasticity) in the data series, Weighted ARCH- LM(auto-regressive conditional heteroscedasticity-Lagrange Multiplier) Test was conducted on 1 lag.

	A1	E1	N1	N3	S1	S2	W1	W3
WGT_RESID^2(-1)	0.26	0.95	0.78	0.78	0.53	0.99	0.52	0.27

Table 4.9: Weighted ARCH- LM test statistics for EGARCH (Exponential GARCH) (1,1)

In the table above, it has been observed that the p-value for 1 lag is above .05, indicating that the ARCH process is an adequate fit and presence of volatility clustering is there, and we cannot reject the null hypothesis.

4.1.3.2 WEIGHTED LJUNG BOX TEST ON STANDARDIZED SQUARED RESIDUALS

Weighted Ljung Box Test on Standardized Squared Residuals was conducted on 6 lags to check the robustness of the model by investig\ating the presence of serial correlation in the residual and square of residual.

Lags	A1	E1	N1	N3	S1	S2	W1	W3
1	0.261	0.949	0.781	0.78	0.533	0.996	0.489	0.257
2	0.228	0.987	0.426	0.474	0.488	0.689	0.413	0.164
3	0.242	0.999	0.566	0.545	0.548	0.857	0.422	0.189
4	0.137	1	0.672	0.628	0.62	0.733	0.364	0.219
5	0.216	1	0.699	0.625	0.753	0.847	0.309	0.281
6	0.275	1	0.804	0.744	0.761	0.887	0.417	0.391

Table 4.10: Weighted Ljung Box Test on Standardized Squared Residuals.

Weighted Ljung Box Test on Standardized Squared Residuals was conducted on all the bid areas as shown in the table above. It has been observed that for the first 6 lags the residuals were not auto-correlated (as p>.05) for all the bid areas. Hence no serial correlation was present in the data series.

4.1.4 THE BEST FIT MODEL

On the basis of the lowest AIC (Akaike information criterion), SIC (Schwarz information criterion), and HQC (Hannan Quinn) value the best fit model is identified. The values of each model are illustrated in Table 4.11.

Bid Area	Model	Akaike info criterion	Schwarz info criterion	Hannan-Quinn criterion
A1	GARCH (1,1)	**0.08**	**0.09**	**0.08**
	EGARCH(1,1)	0.10	0.11	0.10
E1	GARCH (1,1)	**0.10**	**0.11**	**0.11**
	EGARCH (1,1)	0.18	0.19	0.18
N1	GARCH (1,1)	**-0.07**	**-0.06**	**-0.07**
	EGARCH (1,1)	-0.04	-0.03	-0.04
N3	GARCH (1,1)	**-0.07**	**-0.06**	**-0.07**
	EGARCH (1,1)	-0.04	-0.03	-0.03
S1	GARCH (1,1)	0.74	0.75	**0.74**
	EGARCH (1,1)	0.74	0.75	0.75
S2	GARCH (1,1)	0.98	**0.98**	0.98
	EGARCH (1,1)	0.98	0.99	0.98
W1	GARCH (1,1)	**-0.04**	**-0.04**	**-0.04**
	EGARCH (1,1)	-0.02	-0.01	-0.02
W3	GARCH (1,1)	0.09	0.09	0.09
	EGARCH (1,1)	0.11	0.12	0.12

Table 4.11:Information criterion of GARCH (1,1) and EGARCH (1,1)

The above table states that since the value of AIC, SIC, and HQC is lowest for GARCH (generalized auto-regression conditional heteroscedasticity) (1,1) model for each bid area, except for bid areas S1 (where the values for AIC and SIC are same and there is very less difference between the HQC values of both the models) and S2 (where the values for AIC and HQC are same and there is very less difference between the SIC values of both the models), thereby giving ambiguous results. But overall, the GARCH (1,1) model has a better modeling performance when compared to EGARCH (exponential GARCH) (1,1) in all the bid areas.

4.2 EMPIRICAL RESULTS- STUDY OF FORECASTING OF THE INDIAN ELECTRICITY DAY -AHEAD PRICES

The following paragraphs are divided into discussions on the empirical result of the models applied i.e. GARCH(generalized auto-regressive conditional heteroscedasticity) (1,1), best fit ARIMA(auto-regressive integrated moving average) model and NNAR (neural network auto-regression) model followed by medium term forecasting of prices by each model for the next 25 days.

4.2.1 FORECASTING USING ARIMA MODEL (BOX JENKINS MODEL [1976])

The appropriate AR (auto-regressive) and MA (moving average) terms are identified for each of the energy market prices using the minimum AIC (Akaike information criterion) and SIC (Schwarz information criterion) and the highest log likelihood criterion. Since as mentioned in Chapter 3 that the researcher has taken maximum 3 values of p and 2 values of q with d = 0 (as there is no unit root present in the data), therefore the best fit ARIMA(auto-regressive integrated moving average) model for each model is chosen accordingly.

The AIC, SIC, HQC (Hannan Quinn criterion), log likelihood criterion of each bid area are shown in the tables 4.12 to 4.19 below.

Model	Log L	AIC*	BIC	HQ
(2,2)	**1714.98**	**-1.032**	**-1.0209**	**-1.028**
(3,1)	1714.84	-1.0319	-1.0208	-1.028
(2,1)	1704.08	-1.026	-1.0168	-1.0227
(3,2)	1704.37	-1.025	-1.0121	-1.0204
(1,2)	1683.86	-1.0138	-1.0046	-1.0105
(1,1)	1679.77	-1.0119	-1.0046	-1.0093
(3,0)	1680.2	-1.0116	-1.0024	-1.0083
(2,0)	1675.05	-1.0091	-1.0017	-1.0064
(1,0)	1634.46	-0.9852	-0.9797	-0.9832
(0,2)	434.18	-0.2598	-0.2524	-0.2571
(0,1)	-322.2	0.19638	0.20191	0.19836
(0,0)	-1800.7	1.08858	1.09227	1.0899

Table 4.12: AIC, SIC, HQC values for ARMA parameters for E1.

Model	LogL	AIC*	BIC	HQ
(3,1)	**1755.14**	**-1.06**	**-1.05**	**-1.05**
(2,2)	1755.11	-1.06	-1.05	-1.05
(2,1)	1749.14	-1.05	-1.04	-1.05
(3,2)	1749.22	-1.05	-1.04	-1.05
(1,2)	1721.26	-1.04	-1.03	-1.03
(3,0)	1717.16	-1.03	-1.02	-1.03
(1,1)	1715.97	-1.03	-1.03	-1.03
(2,0)	1712.49	-1.03	-1.02	-1.03
(1,0)	1683.94	-1.02	-1.01	-1.01
(0,2)	509.16	-0.31	-0.30	-0.30
(0,1)	-259.97	0.16	0.16	0.16
(0,0)	-741.31	1.05	1.06	1.05

Table 4.13: AIC, SIC, HQC values for ARMA parameters for A1.

Model	Log L	AIC*	BIC	HQ
(3,2)	**2002.96**	**-1.21**	**-1.19**	**-1.20**
(3,1)	1997.86	-1.20	-1.19	-1.20
(2,2)	1997.71	-1.20	-1.19	-1.20
(2,1)	1995.27	-1.20	-1.19	-1.20
(1,1)	1958.51	-1.18	-1.17	-1.18
(1,2)	1959.45	-1.18	-1.17	-1.18
(2,0)	1957.99	-1.18	-1.17	-1.18
(3,0)	1958.55	-1.18	-1.17	-1.18
(1,0)	1945.71	-1.17	-1.17	-1.17
(0,2)	656.65	-0.39	-0.39	-0.39
(0,1)	-122.33	0.08	0.08	0.08
(0,0)	-1705.70	1.03	1.03	1.03

Table 4.14: AIC, SIC, HQC values for ARMA parameters for N1.

Model	Log L	AIC*	BIC	HQ
(3,2)	**1802.91**	**-1.09**	**-1.08**	**-1.09**
(2,0)	1782.24	-1.08	-1.07	-1.08
(2,1)	1782.90	-1.08	-1.07	-1.08
(1,1)	1781.59	-1.08	-1.07	-1.08
(3,0)	1782.55	-1.08	-1.07	-1.08
(2,2)	1783.02	-1.08	-1.07	-1.07
(3,1)	1782.97	-1.08	-1.07	-1.07
-12	1781.89	-1.08	-1.07	-1.08
(1,0)	1759.13	-1.07	-1.06	-1.06
(0,2)	574.51	-0.35	-0.34	-0.34
(0,1)	-214.65	0.13	0.14	0.13
(0,0)	-1694.50	1.03	1.03	1.03

Table 4.15: AIC, SIC, HQC values for ARMA parameters for N3.

Model	Log L	AIC*	BIC	HQ
(2,2)	**1765.98**	**-1.06**	**-1.05**	**-1.06**
(3,1)	1765.96	-1.06	-1.05	-1.06
(3,2)	1765.98	-1.06	-1.05	-1.06
(2,1)	1762.56	-1.06	-1.05	-1.06
(1,2)	1748.86	-1.05	-1.04	-1.05
(3,0)	1745.68	-1.05	-1.04	-1.05
(1,1)	1743.44	-1.05	-1.04	-1.05
(2,0)	1739.57	-1.05	-1.04	-1.05
(1,0)	1710.53	-1.03	-1.03	-1.03
(0,2)	288.77	-0.17	-0.16	-0.17
(0,1)	-515.59	0.31	0.32	0.32
(0,0)	2073.94	1.25	1.26	1.25

Table 4.16: AIC, SIC, HQC values for ARMA parameters for S1.

Model	Log L	AIC*	BIC	HQ
(2,2)	**1765.98**	**-1.06**	**-1.05**	**-1.06**
(3,1)	1765.96	-1.06	-1.05	-1.06
(3,2)	1765.98	-1.06	-1.05	-1.06
(2,1)	1762.56	-1.06	-1.05	-1.06
(1,2)	1748.86	-1.05	-1.04	-1.05
(3,0)	1745.68	-1.05	-1.04	-1.05
(1,1)	1743.44	-1.05	-1.04	-1.05
(2,0)	1739.57	-1.05	-1.04	-1.05
(1,0)	1710.53	-1.03	-1.03	-1.03
(0,2)	288.77	-0.17	-0.16	-0.17
(0,1)	-515.59	0.31	0.32	0.32
(0,0)	-2073.94	1.25	1.26	1.25

Table 4.17:AIC, SIC, HQC values for ARMA parameters for S2.

Model	Log L	AIC*	BIC	HQ
(3,1)	**2006.48**	**-1.21**	**-1.20**	**-1.20**
(2,1)	2001.48	-1.21	-1.20	-1.20
(3,2)	2002.59	-1.21	-1.19	-1.20
(2,2)	1980.60	-1.19	-1.18	-1.19
(1,2)	1976.38	-1.19	-1.18	-1.19
(3,0)	1974.09	-1.19	-1.18	-1.19
(1,1)	1972.28	-1.19	-1.18	-1.19
(2,0)	1970.03	-1.19	-1.18	-1.18
(1,0)	1949.26	-1.18	-1.17	-1.17
(0,2)	630.81	-0.38	-0.37	-0.38
(0,1)	-161.15	0.10	0.10	0.10
(0,0)	-1727.03	1.04	1.05	1.05

Table 4.18: AIC, SIC, HQC values for ARMA parameters for W1.

Model	Log L	AIC*	BIC	HQ
(2,2)	**1703.85**	**-1.03**	**-1.01**	**-1.02**
(3,1)	1703.55	-1.03	-1.01	-1.02
(2,1)	1700.41	-1.02	-1.01	-1.02
(3,2)	1701.56	-1.02	-1.01	-1.02
(1,2)	1676.73	-1.01	-1.00	-1.01
(3,0)	1670.98	-1.01	-1.00	-1.00
(1,1)	1665.39	-1.00	-1.00	-1.00
(2,0)	1661.86	-1.00	-0.99	-1.00
(1,0)	1643.03	-0.99	-0.98	-0.99
(0,2)	410.51	-0.25	-0.24	-0.24
(0,1)	-348.30	0.21	0.22	0.21
(0,0)	-1877.73	1.14	1.14	1.14

Table 4.19:AIC, SIC, HQC values for ARMA parameters for W3.

According to the tables above, the researcher has applied ARIMA (3,0,1), ARIMA (2,0,2), ARIMA(3,0,2), ARIMA(3,0,2), ARIMA(2,0,2), ARIMA(2,0,2), ARIMA(2,0,2), ARIMA(3,0,1), and ARIMA(2,0,2) model on the A1, E1, N1, N3, S1, S2, W1, and W3 market respectively (marked in bold). The results of the estimated ARIMA models are shown in Table 4.20 and 4.21 below. The AR and MA terms are significant at 1% level of significance, indicating the existence of significant auto-correlation, which is considered to be one of the basic requisites for the ARIMA estimation.

The developed ARMA models are checked for auto-correlation using Durbin-Watson statistics and the results are shown in Table 4.20 and 4.21, which indicate that the developed models do not suffer from auto-correlation and the residuals of each market prices are said to be white noise. Therefore, the model developed is a good fit.

Electricity Market	A1	E1	N1	N3
Model	ARIMA (3 0 1)	ARIMA (2 0 2)	ARIMA (3 0 2)	ARIMA (3 0 2)
Parameter	Coefficient	Coefficient	Coefficient	Coefficient
C	8.089554* (60.18907)	8.092645* (39.02653)	8.151971* (50.79357)	8.167195* (52.68511)
AR(1)	1.740214* (148.4121)	1.853941* (774.1412)	0.911455* (29.17049)	0.881751* (18.38339)
AR(2)	-0.670407* (-34.12362)	-0.854328* (-344.9459)	0.853469* (15.21335)	0.926397* (10.57829)
AR(3)	-0.070502* (-5.326973)	--	-0.765659* (-26.62785)	-0.808878* (-19.38640)
MA(1)	-0.958494* (-122.3403)	-1.094778* (-117.2846)	-0.021781 (-0.811387)	-0.005231 (-0.115271)
MA(2)	--	0.122490* (12.96111)	-0.917676* (-35.00238)	-0.941513* (-21.62753)
Residual Diagnostics				
D-W Stat.	2.000414	2.000731	2.096135	2.140689

Notes: Figures in parenthesis are t-statistics. * - denote the significance at 1% level.

Table 4.20: Results of estimated ARIMA models for A1, E1, N1, and N3 electricity market.

Electricity Market	S1	S2	W1	W3
Model	ARIMA (2 0 2)	ARIMA (2 0 2)	ARIMA (3 0 1)	ARIMA (2 0 2)
Parameter	Coefficient	Coefficient	Coefficient	Coefficient
C	4829.284* (12.29586)	5140.880* (8.157904)	8.088684* (53.03853)	8.065563* (43.62024)
AR(1)	0.186327* (3.449800)	1.823744* (46.84971)	1.777615* (207.1823)	1.840187* (279.9473)
AR(2)	0.755106* (14.72970)	-0.825992* (-21.80746)	-0.717167* (-44.36614)	-0.840662* (-128.0687)
AR(3)	--	--	-0.060953* (-5.034284)	--
MA(1)	0.617129* (11.47574)	-1.142894* (-28.58351)	-0.964438* (-140.0653)	-1.033279* (-90.19080)
MA(2)	-0.182631* (-17.19159)	0.209136* (10.80161)	--	0.065826* (6.410616)
Residual Diagnostics				
D-W Stat.	1.995282	1.995984	2.000844	1.997238

Notes: Figures in parenthesis are t-statistics. * - denote the significance at 1% level.

Table 4.21: Results of estimated ARIMA models for S1, S2, W1, and W3 electricity market.

4.2.2 FORECASTING USING GARCH MODEL

Since the researcher has already tested the data set for stationarity hence as a preliminary step, Engle (1982) ARCH-LM (Auto-regressive conditional heteroscedasticity Lagrange Multiplier) test statistics were performed to examine the null hypothesis of no ARCH effects on the all the bid area's price series and its result are provided in Table 4.22. The ARCH-LM test statistics are highly significant at 1% level, confirming the existence of significant ARCH effects on the respective price series, hence the presence of ARCH effects in the residuals of price series warrant for the estimation of GARCH(generalized auto-regressive conditional heteroscedasticity) model.

Bid Area	ARCH- LM Stat	Prob. Value
A1	419.7554*	0.0000
E1	399.2304*	0.000
N1	129.1294*	0.000
N3	253.3425*	0.000
S1	433.3411*	0.000
S2	440.3243*	0.000
W1	508.1369*	0.000
W3	482.6463*	0.000

Note: * denotes significant at 1% level. ARCH-LM is a Lagrange Multiplier test which examines the null hypothesis of ARCH effects in the residuals (Engle, 1982).

Table 4.22: ARCH- LM Test Results

Now, the GARCH models are developed for each electricity market and the results are provided in Table 4.23 and 4.24. The ARCH (α_i) and GARCH (β_j) coefficients are variance equations which are positive and significant at 1% level in all estimations, suggesting the presence of the ARCH and GARCH effects. The result of the Table 4.23 illustrates that the sum of $\alpha + \beta$ coefficients are close to unity, suggesting that the conditional variance is highly persistent and takes a longer period to settle down. This indicates a covariance stationary model with a high degree of persistence and long memory in the conditional variance.

Bid Area	A1	E1	N1	N3
Model	GARCH (1 1)	GARCH (1 1)	GARCH (1 1)	GARCH (1 1)
Parameter	Coefficient	Coefficient	Coefficient	Coefficient
a_0	0.357526* (10.89661)	0.316715* (10.17716)	0.433685* (12.94598)	0.936159* (257.0155)
a_1	0.954857* (236.3631)	0.960352* (251.3208)	0.945545* (229.8319)	0.509211* (17.02932)
α_0	0.001136* (13.54722)	0.007263* (27.97584)	0.000768* (10.10274)	0.000838* (11.10631)
α_i	0.176188* (25.41013)	0.364639* (29.76666)	0.134913* (14.59782)	0.160888* (16.34011)
β_j	0.788126* (109.4896)	0.329220* (16.28978)	0.831956* (83.45084)	0.811845* (88.14578)
Residual Diagnostics				
ARCH-LM Stat.	1.532116 (0.1406)	0.072376 (0.7879)	1.246966 (0.235496)	1.678177 (0.1720)

Notes: Figures in parenthesis are z-statistics. * - denote the significance at 1% level.

Table 4.23: Results of estimated GARCH model for A1, E1, N1, and N3 electricity market.

Bid Area	S1 Market	S2 Market	W1 Market	W3 Market
Model	GARCH (1 1)	GARCH (1 1)	GARCH (1 1)	GARCH (1 1)
Parameter	Coefficient	Coefficient	Coefficient	Coefficient
a_0	0.314554* (10.50516)	0.327229* (9.461780)	0.340249* (11.59110)	0.355709* (12.46457)
a_1	0.962373* (274.1409)	0.961063* (239.7886)	0.957018* (264.3251)	0.954958* (268.2340)
α_0	0.008744* (24.57671)	0.002000* (17.18164)	0.000843* (11.18153)	0.001148* (13.06694)
α_i	0.417311* (30.16336)	0.150256* (21.67537)	0.189011* (17.36952)	0.179635* (20.88229)
β_j	0.212313* (9.197607)	0.786021* (90.05309)	0.782175* (62.29871)	0.783433* (78.71186)
Residual Diagnostics				
ARCH-LM Stat.	0.064029 (0.8003)	0.721751 (0.2499)	1.349265 0.2208	0.561553 (0.9328)

Notes: Figures in parenthesis are z-statistics. * - denote the significance at 1% level.

Table 4.24: Results of estimated GARCH Model for S1, S2, W1, and W3 electricity market.

To check the robustness of the estimated GARCH (1 1) models, the Lagrange Multiplier (ARCH-LM) test was used to test whether the ARCH effects are present in the standardized residuals as shown in Table 4.24. The insignificant

ARCH-LM statistics for all the energy markets confirm that estimated GARCH models are suitably defined and there is no ARCH effect present in the standardized residual.

4.2.3 FORECASTING USING NNAR MODEL OF ARTIFICIAL NEURAL NETWORK

While applying the model, the researcher has trained the model with data from 1 August 2008 to 31 December 2016 (90 % of the data) and tested from 1 January 2017 to 31 August 2017. The NNAR(neural network auto-regression)(p, P, K) model is used wherein the value of p states the value of ARIMA(auto-regression integrated moving average), P states the presence of seasonality or not.; K states the number of hidden layers. Since NN (neural networks) usually have no underlying statistical model, AIC/BIC (Akaike information criterion/ Bayesian information criterion) does not make sense.

NNAR (30,1,16) $_{[365]}$ using ARIMA (30,0,0) with 1 seasonality, 16 hidden layers and 365 number of days is applied wherein 31 daily inputs with 16 hidden layers, 529 weight options, and 68340 as σ^2 are used to get a single output. The results of the NNAR model are as follows:

Bid Area	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1	Dataset
A1	-0.99	261.86	188.08	-1.09	6.79	0.55	-0.01	Training
A1	205.65	255.49	225.79	8.29	9.25	0.67		Test
E1	-1.49	245.50	178.15	-1.19	6.83	0.55	-0.01	Training
E1	198.99	246.07	212.58	8.01	8.65	0.65		Test
N1	0.02	263.54	188.91	-0.97	6.59	0.57	-0.01	Training
N1	469.69	632.70	488.24	15.22	16.09	1.46		Test
N3	-0.51	290.97	199.92	-1.14	6.83	0.56	0.01	Training
N3	372.75	531.59	393.79	11.88	12.86	1.10		Test
S1	-2.46	468.59	302.61	-1.31	7.18	0.67	-0.02	Training
S1	167.28	348.93	297.22	4.90	10.32	0.66		Test
S2	-0.77	709.37	440.43	-2.05	9.27	0.76	0.01	Training
S2	-134.82	260.15	226.15	-5.39	8.18	0.39		Test
W1	0.04	227.21	167.93	-0.82	6.18	0.54	-0.01	Training
W1	212.89	259.93	226.46	8.61	9.25	0.72		Test
W3	-1.50	247.50	180.37	-1.16	6.94	0.55	-0.01	Training
W3	209.57	262.13	230.71	8.43	9.44	0.71		Test

Table 4.25: Results of NNAR (30,1,16) $_{[365]}$ model.

In Table 4.25, the error values of each bidding area attained during testing and training is reflected.

4.2.4 BEST FIT MODEL

In order to find the best fit model for forecasting, the comparison between the error terms of each model is done to check the robustness of each model.

The Table 4.26 to 4.29 below shows the comparison of RMSE (root mean square error), MAE (mean absolute error), MAPE (mean absolute percentage error), and Theil inequality coefficient (TIC) as the statistic values to measure the forecasting performance. The RMSE statistic and MAE statistic depend on the scale of the variable under consideration whereas MAPE statistic and Theil inequality coefficient statistic are not dependent on the same. Forecasting performance of three models has been compared and as a rule of thumb, the model with the lowest value of error statistic is considered to be superior in terms of the forecasting performance.

Error Statistic	A1			E1		
	ARIMA (3 0 1)	**GARCH (1 1)**	**NNAR**	**ARIMA (2 0 2)**	**GARCH (1 1)**	**NNAR**
RMSE	1852.92	1431.32	**255.49**	1790.79	1777.66	**246.07**
MAE	1051.57	870.12	**225.79**	1053.45	1067.38	**212.58**
MAPE	25.25	24.37	**9.25**	28.20	29.37	**8.65**
TIC	0.28	0.20		0.26	0.26	

Table 4.26: Medium term forecasting performance of different models attuned for A1 and E1 of the Indian electricity market.

Error Statistic	N1			N3		
	ARIMA (3 0 2)	**GARCH (1 1)**	**NNAR**	**ARIMA (3 0 2)**	**GARCH (1 1)**	**NNAR**
RMSE	1947.78	1446.30	**632.70**	2006.97	1405.98	**531.59**
MAE	1079.42	839.43	**488.24**	1108.73	821.44	**393.79**
MAPE	24.41	22.18	**16.09**	23.97	21.46	**12.86**
TIC	0.28	0.19		0.29	0.18	

Table 4.27: Medium term forecasting performance of different models attuned for N1 and N3 of the Indian electricity market.

Error Statistic	S1			S2		
	ARIMA (2 0 2)	**GARCH (1 1)**	**NNAR**	**ARIMA** (2 0 2)	**GARCH (1 1)**	**NNAR**
RMSE	2554.88	2353.51	**348.93**	2575.33	2554.88	**260.15**
MAE	1977.94	1744.86	**297.22**	1983.49	1977.94	**226.15**
MAPE	42.53	38.48	**10.32**	41.95	42.53	**8.18**
TIC	0.25	0.24		0.25	0.25	

Table 4.28: Medium term forecasting performance of different models attuned for S1 and S2 of the Indian electricity market.

Error Statistic	W1			W3		
	ARIMA (3 0 1)	**GARCH (1 1)**	**NNAR**	**ARIMA (2 0 2)**	**GARCH (1 1)**	**NNAR**
RMSE	1842.77	1766.86	**259.93**	1868.00	1392.67	**262.13**
MAE	1027.03	1057.60	**226.46**	1051.92	828.05	**230.71**
MAPE	24.69	28.47	**9.25**	26.51	24.24	**9.44**
TIC	0.28	0.26		0.29	0.20	

Table 4.29:Medium term forecasting performance of different models attuned for W1 and W3 of the Indian electricity market

In the above tables it has been observed that for all the bid areas, the NNAR model has the best forecasting performance having the lowest RMSE statistic of 255.49, MAE statistic of 225.79, MAPE statistic of 9.25% for *A1*; lowest RMSE statistic of 246.07, MAE statistic of 212.58, MAPE statistic of 8.65% for *E1*; lowest RMSE statistic of 632.70, MAE statistic of 488.24, MAPE statistic of 16.09% for *N1*; lowest RMSE statistic of 531.59, MAE statistic of 393.79, MAPE statistic of 12.86% for *N3*; lowest RMSE statistic of 348.93, MAE statistic of 297.22, MAPE statistic of 10.32% for *S1*; lowest RMSE statistic of 260.15, MAE statistic of 226.15, MAPE statistic of 8.18% for *S2*; lowest RMSE statistic of 259.93, MAE statistic of 226.46, MAPE statistic of 9.25% for *W1*; and lowest RMSE statistic of 262.13, MAE statistic of 230.71, MAPE statistic of 9.44% for *W3*. In the existing body of literature, there is no rule or standard set by the industry to measure forecasting performance. Still, the Indian electricity day- ahead market prices can be forecasted precisely for all the bid areas with MAPE statistic values hovering around 8-10% which is fairly good (Nogales, Contreras, Conejo and Espinola, 2002; Weron, 2006) except for N1 and N2 with MAPE statistic of around 16% and 12% respectively which is still better than the other two models applied.

4.2.5 MEDIUM FORECASTING BY EACH MODEL

In order to check the authenticity and robustness of the NNAR(neural network auto-regression) model, forecasting of the electricity prices for the next 25 days was conducted as illustrated in Table 4.30.

Particulars	Point Forecast	Lo95	Hi95	Actual	PE	Period
A1	2880.96	2409.12	3371.19	2973.40	3.11	20170901
	2918.54	2301.43	3488.53	2616.24	-11.55	20170902
	2646.33	1992.63	3351.17	2658.73	0.47	20170903
	3195.89	2439.10	3942.19	3247.07	1.58	20170904
	3075.73	2364.21	3911.34	3504.84	12.24	20170905
	3041.93	2348.64	3900.77	3731.00	18.47	20170906
	2884.33	2133.03	3797.62	3949.98	26.98	20170907
	2737.10	2156.91	3573.02	4058.37	32.56	20170908
	2983.55	2349.42	3689.11	4663.61	36.02	20170909
	2641.01	2004.41	3422.07	4397.50	39.94	20170910
	2936.56	2269.07	3788.97	5084.37	42.24	20170911
	2893.09	2199.76	3796.25	5229.85	44.68	20170912
	2963.16	2317.76	3803.82	5138.04	42.33	20170913
	3098.16	2332.99	4078.13	5049.07	38.64	20170914
	3255.89	2293.45	4428.77	5421.67	39.95	20170915
	3199.88	2341.10	4369.88	5532.64	42.16	20170916
	2743.71	1918.85	3993.04	3938.42	30.33	20170917
	2998.44	2183.78	4032.68	5032.88	40.42	20170918
	2811.31	2012.86	3958.27	3856.84	27.11	20170919
	2870.71	2043.48	4037.81	4333.42	33.75	20170920
	2834.73	1998.14	4126.11	4293.64	33.98	20170921

Particulars	Point Forecast	Lo95	Hi95	Actual	PE	Period
	2758.77	1944.25	4274.15	3557.38	22.45	20170922
	2797.86	2000.62	4209.77	3216.63	13.02	20170923
	2578.66	1836.12	3959.41	3014.56	14.46	20170924
	2881.35	2105.74	4129.67	3699.93	22.12	20170925
E1	2880.96	2409.12	3371.19	2973.40	3.11	20170901
	2918.54	2301.43	3488.53	2616.24	-11.55	20170902
	2646.33	1992.63	3351.17	2658.73	0.47	20170903
	3195.89	2439.10	3942.19	3247.07	1.58	20170904
	3075.73	2364.21	3911.34	3504.84	12.24	20170905
	3041.93	2348.64	3900.77	3731.00	18.47	20170906
	2884.33	2133.03	3797.62	3949.98	26.98	20170907
	2737.10	2156.91	3573.02	4058.37	32.56	20170908
	2983.55	2349.42	3689.11	4663.61	36.02	20170909
	2641.01	2004.41	3422.07	4397.50	39.94	20170910
	2936.56	2269.07	3788.97	5084.37	42.24	20170911
	2893.09	2199.76	3796.25	5229.85	44.68	20170912
	2963.16	2317.76	3803.82	5138.04	42.33	20170913
	3098.16	2332.99	4078.13	5049.07	38.64	20170914
	3255.89	2293.45	4428.77	5421.67	39.95	20170915
	3199.88	2341.10	4369.88	5532.64	42.16	20170916
	2743.71	1918.85	3993.04	3938.42	30.33	20170917
	2998.44	2183.78	4032.68	5032.88	40.42	20170918
	2811.31	2012.86	3958.27	3856.84	27.11	20170919
	2870.71	2043.48	4037.81	4333.42	33.75	20170920
	2834.73	1998.14	4126.11	4293.64	33.98	20170921
	2758.77	1944.25	4274.15	3557.38	22.45	20170922
	2797.86	2000.62	4209.77	3216.63	13.02	20170923
	2578.66	1836.12	3959.41	3014.56	14.46	20170924
	2881.35	2105.74	4129.67	3699.93	22.12	20170925
N1	2926.30	2499.78	3441.03	2973.40	1.58	20170901
	2988.74	2401.71	3646.44	2616.24	-14.24	20170902

Particulars	Point Forecast	Lo95	Hi95	Actual	PE	Period
	2567.04	1952.38	3320.70	2658.73	3.45	20170903
	3078.21	2404.64	3890.18	3247.07	5.20	20170904
	2875.01	2144.59	3719.33	3504.84	17.97	20170905
	2891.32	2164.92	3859.72	3731.00	22.51	20170906
	2984.51	2254.95	4043.59	3949.98	24.44	20170907
	2826.22	2146.41	3788.32	4058.37	30.36	20170908
	2925.34	2272.03	3811.28	4663.61	37.27	20170909
	2557.41	1913.38	3451.26	4397.50	41.84	20170910
	2928.42	2220.37	3937.92	5084.37	42.40	20170911
	2836.85	2138.90	3899.83	5229.85	45.76	20170912
	2894.03	2191.99	3997.73	5138.04	43.67	20170913
	2844.15	2106.55	4171.22	5049.07	43.67	20170914
	2908.53	2179.07	4387.22	5421.67	46.35	20170915
	2949.97	2253.43	4451.40	5532.64	46.68	20170916
	2470.17	1766.43	4056.39	3938.42	37.28	20170917
	2695.19	2038.71	4092.91	5032.88	46.45	20170918
	2534.21	1785.69	3921.73	3856.84	34.29	20170919
	2636.12	1889.19	4127.53	4333.42	39.17	20170920
	2669.59	1919.74	4237.88	4293.64	37.82	20170921
	2656.86	1833.05	4358.31	3557.38	25.31	20170922
	2638.05	1828.03	4325.26	3216.63	17.99	20170923
	2331.69	1691.97	4002.23	3014.56	22.65	20170924
	2607.45	1891.76	4246.61	3699.93	29.53	20170925
N3	2822.71	2331.10	3321.48	2973.40	5.07	20170901
	2877.18	2267.54	3495.13	2616.24	-9.97	20170902
	2552.51	1810.80	3283.61	2658.73	4.00	20170903
	3007.88	2325.12	3795.72	3247.07	7.37	20170904
	2951.82	2225.34	3779.99	3504.84	15.78	20170905
	3006.89	2263.69	3912.91	3731.00	19.41	20170906
	2996.73	2190.32	3951.44	3949.98	24.13	20170907
	2916.93	2104.80	3844.22	4058.37	28.13	20170908

Particulars	Point Forecast	Lo95	Hi95	Actual	PE	Period
	2875.94	2086.82	3734.79	4663.61	38.33	20170909
	2572.66	1838.26	3450.83	4397.50	41.50	20170910
	3004.09	2233.47	3933.69	5084.37	40.92	20170911
	2977.27	2203.71	3929.26	5229.85	43.07	20170912
	3083.96	2295.49	3992.88	5138.04	39.98	20170913
	3050.95	2242.01	4019.60	5049.07	39.57	20170914
	3119.98	2186.36	4252.00	5460.05	42.86	20170915
	3150.71	2180.44	4422.13	5532.64	43.05	20170916
	2626.95	1717.73	3962.22	3938.42	33.30	20170917
	2836.15	1967.02	4175.39	5032.88	43.65	20170918
	2752.97	1914.03	4046.07	3856.84	28.62	20170919
	2809.71	1933.29	4293.56	4333.42	35.16	20170920
	2807.92	1862.17	4369.36	4293.64	34.60	20170921
	2810.31	1817.85	4387.91	3557.38	21.00	20170922
	2853.45	1858.13	4335.61	3216.63	11.29	20170923
	2589.50	1634.85	4040.76	3014.56	14.10	20170924
	2791.26	1835.77	4375.31	3699.93	24.56	20170925
S1	2866.58	2331.78	3398.46	2973.40	3.59	20170901
	3004.88	2352.55	3690.29	2616.24	-14.85	20170902
	2722.63	1888.63	3529.82	2658.73	-2.40	20170903
	3063.65	2179.14	3895.51	3247.07	5.65	20170904
	3048.00	2234.16	3942.92	3504.84	13.03	20170905
	3094.26	2189.48	4147.70	3731.00	17.07	20170906
	3072.55	2204.67	4148.29	3949.98	22.21	20170907
	2942.73	1995.94	4099.27	4058.37	27.49	20170908
	2844.18	1990.36	3906.41	4663.61	39.01	20170909
	2544.59	1733.58	3535.82	4397.50	42.14	20170910
	2921.13	2147.86	4041.13	5084.37	42.55	20170911
	2832.76	1997.06	3934.16	5229.85	45.83	20170912
	2993.73	2065.15	4171.02	5138.04	41.73	20170913
	2934.01	1998.78	4254.87	5049.07	41.89	20170914

Particulars	Point Forecast	Lo95	Hi95	Actual	PE	Period
	3079.03	2177.05	4471.84	5460.05	43.61	20170915
	3151.68	2243.15	4687.37	5532.64	43.03	20170916
	2716.73	1856.37	4402.22	3938.42	31.02	20170917
	2866.11	1989.55	4488.31	5032.88	43.05	20170918
	2788.73	1905.83	4313.60	3856.84	27.69	20170919
	2832.11	1887.00	4525.51	4333.42	34.64	20170920
	2806.85	1844.19	4587.70	4293.64	34.63	20170921
	2779.18	1718.80	4610.64	3557.38	21.88	20170922
	2776.61	1792.16	4630.43	3216.63	13.68	20170923
	2565.32	1653.50	4534.23	3014.56	14.90	20170924
	2714.12	1811.08	4685.81	3699.93	26.64	20170925
S2	2787.36	1889.09	3707.74	2973.40	6.26	20170901
	3012.65	1804.38	4200.42	2616.24	-15.15	20170902
	3064.55	1742.32	4379.28	2658.73	-15.26	20170903
	3123.05	1837.83	4460.27	3247.07	3.82	20170904
	3086.11	1820.42	4526.76	3504.84	11.95	20170905
	3001.02	1726.07	4402.80	3731.00	19.57	20170906
	2991.01	1670.95	4544.86	3949.98	24.28	20170907
	3018.12	1594.89	4721.17	4058.37	25.63	20170908
	3213.35	1823.58	4948.62	4663.61	31.10	20170909
	3044.06	1664.25	4807.26	4397.50	30.78	20170910
	2906.41	1497.19	4763.96	5084.37	42.84	20170911
	2770.26	1461.79	4738.63	5229.85	47.03	20170912
	2854.32	1436.89	4714.13	5138.04	44.45	20170913
	3007.04	1656.18	5010.18	5049.07	40.44	20170914
	3104.99	1673.96	5138.41	5421.67	42.73	20170915
	3118.05	1608.20	5211.78	5532.64	43.64	20170916
	2902.22	1443.24	5002.91	3938.42	26.31	20170917
	2922.35	1549.06	5228.60	5032.88	41.93	20170918
	2792.38	1383.52	5095.12	3856.84	27.60	20170919
	2902.70	1572.68	5240.77	4333.42	33.02	20170920

Particulars	Point Forecast	Lo95	Hi95	Actual	PE	Period
	2902.93	1540.75	5161.48	4293.64	32.39	20170921
	2850.21	1456.88	5411.66	3557.38	19.88	20170922
	2850.35	1501.56	5507.36	3216.63	11.39	20170923
	2743.46	1301.46	5435.76	3014.56	8.99	20170924
	2795.54	1557.80	5512.51	3699.93	24.44	20170925
W1	2769.19	1461.32	4024.40	2973.40	6.87	20170901
	2902.39	1311.33	4459.58	2616.24	-10.94	20170902
	2934.55	1175.67	4898.01	2658.73	-10.37	20170903
	2840.57	973.10	5133.03	3247.07	12.52	20170904
	2852.22	986.88	5249.56	3504.84	18.62	20170905
	2910.78	900.98	5587.05	3731.00	21.98	20170906
	2858.73	825.46	5664.53	3949.98	27.63	20170907
	2780.27	966.44	5767.22	4058.37	31.49	20170908
	2761.34	983.99	6117.28	4663.61	40.79	20170909
	2581.51	952.89	5999.90	4397.50	41.30	20170910
	2657.43	975.09	6180.33	5084.37	47.73	20170911
	2628.15	1137.12	6243.68	5229.85	49.75	20170912
	2583.40	1258.95	6356.97	5138.04	49.72	20170913
	2598.43	1240.48	6357.17	5049.07	48.54	20170914
	2594.50	1349.72	6407.08	5421.67	52.15	20170915
	2573.84	1310.30	6582.64	5532.64	53.48	20170916
	2500.27	1182.61	6925.14	3938.42	36.52	20170917
	2552.18	1410.62	6843.96	5032.88	49.29	20170918
	2481.37	1335.64	6969.11	3856.84	35.66	20170919
	2485.49	1304.41	6998.95	4333.42	42.64	20170920
	2479.92	1388.94	7239.74	4293.64	42.24	20170921
	2455.67	1444.46	7297.80	3557.38	30.97	20170922
	2476.73	1401.41	7227.97	3216.63	23.00	20170923
	2467.62	1533.55	7190.54	3014.56	18.14	20170924
	2479.11	1638.27	7219.24	3699.93	33.00	20170925
W3	2843.86	2413.38	3310.60	2973.40	4.36	20170901

Particulars	Point Forecast	Lo95	Hi95	Actual	PE	Period
	2944.80	2441.05	3569.34	2616.24	-12.56	20170902
	2658.59	2087.33	3361.67	2658.73	0.01	20170903
	3329.69	2711.36	4071.84	3247.07	-2.54	20170904
	3059.86	2426.59	3954.29	3504.84	12.70	20170905
	2997.00	2332.90	3920.16	3731.00	19.67	20170906
	3044.54	2407.74	4059.58	3949.98	22.92	20170907
	2913.07	2287.00	4021.97	4058.37	28.22	20170908
	2952.08	2370.58	3932.69	4663.61	36.70	20170909
	2669.69	2084.25	3546.69	4397.50	39.29	20170910
	3122.09	2531.77	4080.73	5084.37	38.59	20170911
	3022.60	2326.40	4049.58	5229.85	42.20	20170912
	3128.84	2469.94	4226.37	5138.04	39.10	20170913
	3265.71	2569.43	4570.44	5049.07	35.32	20170914
	3242.30	2469.02	4756.43	5421.67	40.20	20170915
	3265.68	2534.83	4740.12	5532.64	40.97	20170916
	2729.13	2081.10	4153.43	3938.42	30.70	20170917
	2959.33	2368.92	4371.63	5032.88	41.20	20170918
	2713.86	2147.01	4114.67	3856.84	29.64	20170919
	2790.70	2227.43	4128.36	4333.42	35.60	20170920
	2936.21	2270.94	4478.51	4293.64	31.62	20170921
	2874.76	2234.93	4442.80	3557.38	19.19	20170922
	2824.31	2177.21	4403.06	3216.63	12.20	20170923
	2536.45	1908.97	4103.69	3014.56	15.86	20170924
	2902.70	2282.53	4417.20	3699.93	21.55	20170925

Table 4.30: 25 days forecasted values of NNAR(30,1,16)$_{[365]}$ model for each bid area.

In the above-illustrated tables, it has been observed that the point forecast values of NNAR(neural network auto-regression) lie between Lo95 and Hi95 i.e. hypothesis of the value of prediction at 95% confidence interval stating that NNAR is a robust model.

The estimated GARCH (generalized auto-regressive conditional heteroscedasticity), ARIMA (auto-regressive integrated moving average), and NNAR models are used for forecasting the electricity market prices for the next 25 days for each bid area, which have been shown in Table 4.31 – 4.38 below.

Market	A1(Price in Rs./kWh)		
No. of Days	ARIMA	GARCH	NNAR
1	2.82	2.79	2.88
2	2.84	2.79	2.92
3	2.85	2.79	2.65
4	2.86	2.79	3.20
5	2.87	2.78	3.08
6	2.88	2.78	3.04
7	2.89	2.78	2.88
8	2.90	2.78	2.74
9	2.90	2.78	2.98
10	2.91	2.78	2.64
11	2.91	2.78	2.94
12	2.92	2.78	2.89
13	2.92	2.77	2.96
14	2.92	2.77	3.10
15	2.93	2.77	3.26
16	2.93	2.77	3.20
17	2.93	2.77	2.74
18	2.93	2.77	3.00
19	2.93	2.77	2.81
20	2.94	2.77	2.87
21	2.94	2.77	2.83
22	2.94	2.77	2.76
23	2.94	2.77	2.80
24	2.94	2.77	2.58
25	2.94	2.76	2.88

Table 4.31: 25 days forecasted values of the estimated GARCH, ARIMA, and NNAR model for A1.

Market	E1(Price in Rs./kWh)		
No. of Days	**ARIMA**	**GARCH**	**NNAR**
1	2.82	2.80	2.88
2	2.82	2.81	2.92
3	2.83	2.81	2.65
4	2.84	2.82	3.20
5	2.85	2.82	3.08
6	2.85	2.83	3.04
7	2.86	2.83	2.88
8	2.86	2.84	2.74
9	2.86	2.84	2.98
10	2.87	2.84	2.64
11	2.87	2.85	2.94
12	2.87	2.85	2.89
13	2.87	2.86	2.96
14	2.88	2.86	3.10
15	2.88	2.86	3.26
16	2.88	2.87	3.20
17	2.88	2.87	2.74
18	2.88	2.87	3.00
19	2.89	2.87	2.81
20	2.89	2.88	2.87
21	2.89	2.88	2.83
22	2.89	2.88	2.76
23	2.89	2.89	2.80
24	2.89	2.89	2.58
25	2.89	2.89	2.88

Table 4.32:25 days forecasted values of the estimated GARCH, ARIMA, and NNAR model for E1.

Market	N1(Price in Rs./kWh)		
No. of Days	**ARIMA**	**GARCH**	**NNAR**
1	2.78	2.80	2.93
2	2.83	2.80	2.99
3	2.82	2.81	2.57
4	2.86	2.81	3.08
5	2.84	2.81	2.88
6	2.88	2.82	2.89
7	2.86	2.82	2.98
8	2.89	2.82	2.83
9	2.88	2.83	2.93
10	2.90	2.83	2.56
11	2.89	2.83	2.93
12	2.91	2.83	2.84
13	2.90	2.84	2.89
14	2.91	2.84	2.84
15	2.90	2.84	2.91
16	2.92	2.84	2.95
17	2.91	2.84	2.47
18	2.92	2.85	2.70
19	2.91	2.85	2.53
20	2.92	2.85	2.64
21	2.92	2.85	2.67
22	2.93	2.85	2.66
23	2.92	2.85	2.64
24	2.93	2.85	2.33
25	2.93	2.86	2.61

Table 4.33:25 days forecasted values of the estimated GARCH, ARIMA, and NNAR model for N1.

Market	N3 (Price in Rs./kWh)		
No. of Days	**ARIMA**	**GARCH**	**NNAR**
1	2.80	2.80	2.82
2	2.83	2.81	2.88
3	2.83	2.81	2.55
4	2.85	2.82	3.01
5	2.85	2.83	2.95
6	2.87	2.83	3.01
7	2.86	2.84	3.00
8	2.88	2.84	2.92
9	2.88	2.85	2.88
10	2.89	2.85	2.57
11	2.89	2.85	3.00
12	2.90	2.86	2.98
13	2.89	2.86	3.08
14	2.91	2.86	3.05
15	2.90	2.87	3.12
16	2.91	2.87	3.15
17	2.91	2.87	2.63
18	2.92	2.87	2.84
19	2.91	2.88	2.75
20	2.92	2.88	2.81
21	2.92	2.88	2.81
22	2.92	2.88	2.81
23	2.92	2.88	2.85
24	2.93	2.89	2.59
25	2.92	2.89	2.79

Table 4.34:25 days forecasted values of the estimated GARCH, ARIMA, and NNAR model for N3.

Market	S1(Price in Rs./kWh)		
No. of Days	**ARIMA**	**GARCH**	**NNAR**
1	2.88	2.84	2.87
2	2.97	2.88	3.00
3	3.01	2.93	2.72
4	3.08	2.97	3.06
5	3.13	3.01	3.05
6	3.19	3.05	3.09
7	3.24	3.09	3.07
8	3.30	3.13	2.94
9	3.35	3.16	2.84
10	3.40	3.20	2.54
11	3.44	3.23	2.92
12	3.49	3.27	2.83
13	3.53	3.30	2.99
14	3.58	3.33	2.93
15	3.62	3.36	3.08
16	3.66	3.39	3.15
17	3.69	3.42	2.72
18	3.73	3.45	2.87
19	3.77	3.77	2.79
20	3.80	3.80	2.83
21	3.84	3.84	2.81
22	3.87	3.87	2.78
23	3.90	3.90	2.78
24	3.93	3.93	2.57
25	3.96	3.96	2.71

Table 4.35:25 days forecasted values of the estimated GARCH, ARIMA, and NNAR model for S1.

Market	S2 (Price in Rs./kWh)		
No. of Days	ARIMA	GARCH	NNAR
1	2.93	2.85	2.79
2	3.01	2.90	3.01
3	3.07	2.94	3.06
4	3.13	2.99	3.12
5	3.19	3.04	3.09
6	3.24	3.09	3.00
7	3.28	3.13	2.99
8	3.32	3.17	3.02
9	3.36	3.22	3.21
10	3.40	3.26	3.04
11	3.43	3.30	2.91
12	3.46	3.34	2.77
13	3.49	3.38	2.85
14	3.52	3.41	3.01
15	3.54	3.45	3.10
16	3.57	3.48	3.12
17	3.60	3.52	2.90
18	3.62	3.55	2.92
19	3.64	3.64	2.79
20	3.66	3.66	2.90
21	3.69	3.69	2.90
22	3.71	3.71	2.85
23	3.73	3.73	2.85
24	3.75	3.75	2.74
25	3.77	3.77	2.80

Table 4.36:25 days forecasted values of the estimated GARCH, ARIMA, and NNAR model for S2.

Market	W1(Price in Rs./kWh)		
No. of Days	**ARIMA**	**GARCH**	**NNAR**
1	2.81	2.79	2.77
2	2.82	2.79	2.90
3	2.84	2.79	2.93
4	2.84	2.79	2.84
5	2.85	2.78	2.85
6	2.86	2.78	2.91
7	2.87	2.78	2.86
8	2.87	2.78	2.78
9	2.88	2.78	2.76
10	2.88	2.77	2.58
11	2.88	2.77	2.66
12	2.89	2.77	2.63
13	2.89	2.77	2.58
14	2.89	2.77	2.60
15	2.90	2.77	2.59
16	2.90	2.77	2.57
17	2.90	2.77	2.50
18	2.90	2.76	2.55
19	2.90	2.90	2.48
20	2.91	2.91	2.49
21	2.91	2.91	2.48
22	2.91	2.91	2.46
23	2.91	2.91	2.48
24	2.91	2.91	2.47
25	2.91	2.91	2.48

Table 4.37:25 days forecasted values of the estimated GARCH, ARIMA, and NNAR model for W1.

Market	W3 (Price in Rs./kWh)		
No. of Days	**ARIMA**	**GARCH**	**NNAR**
1	2.81	2.79	2.84
2	2.82	2.78	2.94
3	2.83	2.78	2.66
4	2.84	2.78	3.33
5	2.85	2.77	3.06
6	2.86	2.77	3.00
7	2.86	2.76	3.04
8	2.87	2.76	2.91
9	2.87	2.76	2.95
10	2.87	2.75	2.67
11	2.88	2.75	3.12
12	2.88	2.75	3.02
13	2.88	2.75	3.13
14	2.88	2.74	3.27
15	2.89	2.74	3.24
16	2.89	2.74	3.27
17	2.89	2.74	2.73
18	2.89	2.73	2.96
19	2.89	2.89	2.71
20	2.89	2.89	2.79
21	2.90	2.90	2.94
22	2.90	2.90	2.87
23	2.90	2.90	2.82
24	2.90	2.90	2.54
25	2.90	2.90	2.90

Table 4.38:25 days forecasted values of the estimated GARCH, ARIMA, and NNAR model for W3.

4.3 CHAPTER SUMMARY

The chapter aimed at answering the research questions of the thesis with detailed methodology and empirical results of the quantitative techniques applied in the bid areas of the Indian electricity day- ahead market. The goal behind studying volatility was to check how much volatility exists in each bid area and whether the data series have long term or short-term shocks. The study of leverage effect was done to check the impact of positive or negative news on the electricity market. To study the volatility and the shocks in the electricity market, the GARCH (generalized auto-regresssion conditional heteroskedasticity) (1,1) model has been applied and the leverage effect was studied by applying EGARCH (exponential GARCH) (1,1) on the data set. A comparison of the two models was also done to find the best fit model to study volatility. It was further concluded that GARCH (1,1) outperforms the other model in terms of studying volatility.

Three models such as GARCH (1,1), best fit ARIMA(auto-regressive integrated moving average) model (found out based on lowest AIC[Akaike information criterion] values) and the NNAR(neural network auto-regression) model was applied on the data series to check the efficacy of each model on the basis of the error statistic values among which NNAR has outperformed the other two models. Also, the medium-term forecasting of the next 25 days was conducted applying each model to check the robustness of the models.

The result would help the risk managers and the power market participants to decide which position to take while trading in the Indian electricity market especially while trading in the southern region, thereby leading to maximization of the profits.

CHAPTER 5
CONCLUSION AND FUTURE RESEARCH

5.0 CHAPTER OVERVIEW

This chapter is a summary of the whole thesis comprising of the major research findings catering to the research objectives, contribution to the existing body of literature, its policy implication, and the limitations of the research. Some suggestions for future scope of work are also made for the budding researchers, who are willing to conduct studies in the Indian electricity market.

5.1 SUMMARY OF RESEARCH FINDINGS

The major findings of this research are as follows:

1) One of the major risks which needs to be addressed while studying the Indian electricity market is price risk/ extreme volatility.
2) During the monthly analysis of the electricity price determinants, it has been observed that since August 2008, the maximum frequency of occurrence of volatility between 10-30% has been in all the regions except the southern region due to regulatory changes, less coal supply, congestion in the transmission lines, and seasonal variations. The occurrence of volatility between 30-70% has taken place in the southern region due to regulatory and weather changes, transmission congestion, elections, power plant outage, and new power plants operational. Furthermore, there were two incidents in March 2010 and October 2011, which have led to a phenomenal rise in the IEX (Indian Electricity Exchange) prices by 89.5% in S2 and S3 and 104 % in S1 due to regulatory and weather changes in March 2010 and by 103 % in the southern region due to flooding of coal mines in Orissa leading to strike in the coal mines respectively. Thus, the various reasons behind the huge price movement in the electricity prices mentioned in the existing literature, there are few reasons only which

govern the electricity market, i.e. regulatory, weather changes, transmission congestion, elections, power plant outage, fuel supply, and new power plants operational.

3) During the study, it has been observed that the volatility in the southern region was highest from the year 2008 to 2017 as the standard deviation is at its peak in the southern region and lowermost in north- eastern region. The range of prices is highest in the southern region and lowest in the northern region. The data series is positively skewed, it shows that the chance of prices going up in all the regions is comparatively higher than the mean rather than going down. The reason behind the prices going up is due to congestion in the transmission corridor. The kurtosis for each bid area is more than 3, hence the data is leptokurtic i.e. it is dispersed away from the mean.

4) While applying the GARCH (generalized auto-regression conditional heteroscedasticity) model in the data set, the following observations were made:

a.) The data series has no unit root and no presence of serial correlation there.

b.) For all the bid areas (except S1), the total of alpha1 and beta1 is lesser than 1, indicating the presence of mean reversion in the data. Since the sum is closer to 1, the reversion process will be quite slow. Whereas in the case of S1, the sum of both the parameters is equal to 1, stating that further EGARCH (exponential GARCH) model needs to be applied on the bidding area.

5) While applying EGARCH model on the data set, it was found that:

a.) In the bid areas S1 and S2, there is a negative leverage effect stating that the impact of bad news (transmission, congestion and weather) is more than good news thereby leading to high volatility that too in a negative direction. Whereas in other bid areas, chances of volatility are less, and positive news has more impact than negative news.

b.) The analysis also suggests that the past variances have an impact on the present data i.e. study of historical prices play an important role in determining the electricity prices in the future.

6) While doing a comparative study of the GARCH (1,1) and the EGARCH (1,1) model in each of the bid areas, GARCH (1,1) model outperformed the other model. Except for bid areas S1 (where the values for AIC [Akaike information criterion and SIC Schwarz information criterion] are same and there is very less difference between the HQC [Hannan Quinn] values of both the models) and S2 (where the values for AIC and HQC are same and there is very less difference between the SIC values of both the models), thereby giving ambiguous results. But overall, the GARCH (1,1) model has a better modeling performance when compared to EGARCH (1,1) in all the bid areas.

7) While applying ARIMA(auto-regression integrated moving average) model for forecasting, the researcher has used ARIMA (3,0,1), ARIMA (2,0,2), ARIMA (3,0,2), ARIMA (3,0,2), ARIMA (2,0,2), ARIMA (2,0,2), ARIMA (3,0,1) and ARIMA (2,0,2) model on the A1, E1, N1, N3, S1, S2, W1, and W3 market.

8) The NNAR (neural network auto-regression) model was run on R which reflects that there has been a rise in the MAPE (mean absolute percentage error) between the trained and the tested data for A1, E1, N1, N3, S1, W1, and W3 by approx. 36%, 27%, 144%, 88%, 44%, 50%, and 36% respectively and a decrease in S2 by 11 %. The extreme rise in the error in N1 and N3 might be due to overfitting or environmental changes. The northern region of India constitutes of Jammu and Kashmir, Himachal Pradesh, Chandigarh, Haryana, Uttar Pradesh, Uttaranchal, Rajasthan, Delhi, and Punjab. According to the Annual Report 2017-18 of Central Electricity Authority, the percentage of energy not supplied in the northern region is higher in comparison to the other regions, which could also have been a reason for higher percentage increase in the error in the northern region.

9) Among the three models applied to forecast the electricity prices of all the bid areas of the Indian Energy Exchange, NNAR model has the best forecasting performance having the lowest RMSE (root mean square error) statistic of 255.49, MAE(mean absolute error) statistic of 225.79, MAPE (mean absolute percentage error) statistic of 9.25% for *A1*, lowest

RMSE statistic of 246.07, MAE statistic of 212.58, MAPE statistic of 8.65% for *E1*, lowest RMSE statistic of 632.70, MAE statistic of 488.24, MAPE statistic of 16.09% for *N1*, lowest RMSE statistic of 531.59, MAE statistic of 393.79, MAPE statistic of 12.86% for *N3*, lowest RMSE statistic of 348.93, MAE statistic of 297.22, MAPE statistic of 10.32% for *S1*, lowest RMSE statistic of 260.15, MAE statistic of 226.15, MAPE statistic of 8.18% for *S2*, lowest RMSE statistic of 259.93, MAE statistic of 226.46, MAPE statistic of 9.25% for *W1*, and lowest RMSE statistic of 262.13, MAE statistic of 230.71, MAPE statistic of 9.44% for *W3*.

10) In the existing body of literature, there is no rule or standard set by the industry to measure forecasting performance. Still, the Indian electricity day- ahead market prices can be forecasted precisely for all the bid areas with MAPE (mean absolute percentage error) statistic values hovering around 8-10% which is fairly good (Nogales, Contreras, Conejo and Espinola, 2003; Weron, 2006) except for N1 and N2 with MAPE statistic of around 16% and 12% respectively but still better than the other two models applied.
11) Medium- term forecasting of the next 25 days was conducted applying each model to check the robustness of the models.
12) The research displays a larger picture to the investors, policy- makers, and other power market participants about the price risk and which position to take in the future in order to gain maximum profits.

5.2 CONTRIBUTIONS

This research focuses on the means with which volatility and forecasting assessments were made particularly in the Indian Energy Exchange market. Electricity prices generally exhibit seasonality at the annual, monthly, weekly, daily, and intra-day level not only in India but across the globe (Girish and Vijayalakshmi, 2013). In a current deregulated scenario and observing the peculiar features of electricity, the study of volatility and forecasting of electricity demand and price is a matter of interest to market participants (Bunn,2000). According to Weron (2006) & Weron and Misiorek (2005), there are various methods through which the study of volatility and forecasting can be conducted but there has been no research till date (according to my study) which caters to the modeling of each bid area in the Indian Electricity Exchange market. Hence this study includes the application of the most recent and latest time series models to study the behavior of the Indian Electricity Exchange market prices thereby applying upcoming forecasting models as well.

While checking for the presence of unit root test on the data series, the researcher has also applied the Zivot-Andrews sequential break test (1992) to check the presence of structural break in the data series along with the standard unit root tests such as Augmented Dickey-Fuller (ADF) test and Phillips–Perron (PP) test, which has never been applied before in the Indian electricity prices data set.

The researcher has extended the GARCH(generalized auto-regression conditional heteroscedasticity)(1,1) model while studying the volatility of the data set, by applying EGARCH(exponential GARCH)(1,1) model as well to check the leverage effect i.e. the direction in which the electricity market will move in the future. The result is also validated by the qualitative analysis.

In terms of forecasting, apart from the GARCH(1,1) and best fit ARIMA(auto-regressive integrated moving average) models, NNAR(neural network auto-regression) model (one of the latest time series techniques) is also applied to give the better forecasting performance of the Indian Electricity Exchange market prices of each bid area.

The researcher has also conducted medium term forecasting on the data series of each bid area for the next 25 days so that the market participants such as power generators, distribution companies, power traders, and the transmission companies can take either long or short position while trading in the Indian Energy Exchange.

5.3 POLICY IMPLICATIONS

The present research studies the pattern of the Indian Electricity Exchange market prices of each bid area using latest econometric models thereby forecasting the prices for the next 25 days. This study has the following policy implications:

1) With over 4400 open access consumers in Indian electricity market, this study will help the power market stakeholders to understand the working of the Indian day-ahead market and will help them in effective bidding and adopting strategies to meet their short -term and long-term requirements as well as to manage their price risks.
2) The spot prices have a strong affect on the wholesale prices which further rules the retail price for the ultimate customers. Distribution companies in India have accrued losses equal to 4% of India's GDP (gross domestic product) and loses around Rs. 68,000 crore ($10 billion) annually (Patil, April 2017). Through this study, the distribution companies will be able to plan their power purchase cost further helping them in preparation of ARR (annual revenue requirement). These companies will also be able to manage their peak demand, with lesser amount of losses being incurred by them which would further contribute to the betterment of the economy.
3) The study will help the policy- makers take an erudite decision to introduce risk management strategies i.e. electricity derivatives in the Indian power market, which has been successfully adopted in the sophisticated global electricity markets.
4) Through this study the power traders will be able to adopt risk management techniques in both the exchange traded as well as the short-term bilateral market.
5) The deregulation of the Indian electricity markets has posed more policy challenges among the power generators with the aim to set economically efficient prices. The study will help the power generators to make wise investment decisions i.e. whether to invest in the further generation of electricity or to curtail it.

5.4 LIMITATIONS

The major limitations which the researcher has faced while conducting the volatility and the forecasting study of the bid areas of the Indian electricity exchange trade market are as follows:

1) The current study only includes application of the models on the data set from 1st August 2008 to 31st August 2017, although the Indian Energy Exchange have commenced its operations on 27th June 2008. The data of first two months has been excluded for the analysis as in the beginning it has been observed by the power market participants that the market exhibits unusual behavior (Bowden and Payne, 2008; Hadsell, Marathe & Shawky, 2004).
2) Another limitation of the research was lack of availability of the data for some dates of the bid areas. Hence the missing data was eliminated for the successful application of the models which have further led to difference in the observations of the data set of some of the bid areas as mentioned before in the thesis.
3) The researcher has conducted a study using daily data of the Indian Electricity day- ahead market series, which studies spike behavior with a duration of one day each, whereas the electricity market in India has 15-minute time blocks, which are averaged to get the daily prices. Each day consisting of 96-time blocks have strong variations which is yet to be explored, especially when the Indian electricity market works on the Time of the Day concept.
4) While applying the NNAR (neural network auto-regression) model, the number of iterations and neurons in the hidden layer has been selected based on ACF (auto-correlation function) plots in order to avoid the problem of overfitting.
5) While applying the ARIMA (auto-regressive integrated moving average) model, the researcher has taken maximum 3 values of p and 2 values of q with d = 0 as there is no unit root present in the data. This was done to avoid over- fitting whereas other researchers can take different p,d, and q values to run the model.

5.5 SUGGESTIONS FOR FUTURE RESEARCH

- The Indian short-term electricity market constitutes of the bilateral market, exchange-traded market, and DSM (deviation settlement mechanism), whereas this research only studies the prices of the exchange traded market, which leaves a further scope of study in the prices of other two markets.

- The main aim of every power market participant is to hedge against extreme price movements (i.e. spikes or jumps) to earn maximum profits, hence the researcher has left a scope of application of derivatives in the prices of each of the bid areas of the Indian Electricity Exchange traded market.
- The Impact of Renewable Energy Certificate trading on spot electricity prices in India could also be investigated in the future (Shereef and Khaparde, 2013; Girish, Sashikala, Supra and Acharya, 2015).
- One of the distinctive features of electricity prices being volatile leads to the study of various univariate and multivariate price modeling wherein the effect of one region over another can also be studied (Liu, 2013).
- This research has highlighted the factors affecting the electricity prices which can be considered for modeling prices and has given a new dimension of study to conduct research in the power sector. The variables identified such as temperature, water reservoir levels, prices of fuels and regulations can be used to study the impact of each factor on the prices (Janczura, Trueck, Weron and Wolff, 2013; Kaller, Bielen and Marneffe, 2018).

5.6 SPECIFIC CONCLUSION

The Indian Electricity Exchange trade market is subject to huge fluctuations due to which despite the fact that trading through power exchange poses lesser risk, better efficiency and liquidity, the volume traded through it is still low in comparison with other forms of trading i.e. long-term power purchase agreement (PPA), short term contracts. In the current new framework of competitive electricity markets, study of volatility and applying latest forecasting techniques is imperative as huge money is involved in the power trading business and its increasing impact on the Indian economy. The current research aimed at studying the volatility of the Indian day-ahead market prices since its inception, comparing the two well-known volatility models aims to suggest accurate forecasting technique to be applied in the market. The research has displayed a larger picture to the investors, policy- makers, and other power market participants about the price risk and which position to take in the future to gain maximum profits in their respective businesses.

The process of research follows an approach wherein firstly the electricity price determinants were identified by doing a monthly analysis of each factor affecting the prices of the Indian Electricity Exchange trade market. Among the various reasons behind the huge price movement in the electricity prices mentioned in the existing literature, there are few reasons only which governs the electricity market, i.e. Regulatory, weather changes, transmission congestion, elections, power plant outage, fuel supply, and new power plants operational. The research was then followed by answering the research questions of the thesis with detailed methodology and empirical results of the quantitative techniques applied in the prices of the bid areas of the Indian electricity day- ahead market. The goal behind studying volatility was to check how much volatility exists in each bid area and whether the data series have long- term or short-term shocks. The study of leverage effect was done to check the impact of positive or negative news on the electricity market. To study the volatility and the shocks in the electricity market, the GARCH(generalized auto-regression conditional heteroskedasticity) (1,1) model has been applied and the leverage effect was studied by applying EGARCH (exponential GARCH) (1,1) on the data set. A comparison of the two models was also done to find the best fit model to study volatility. It was further concluded that GARCH (1,1) outperforms the other model in terms of studying volatility.

Three models such as GARCH (1,1), best fit ARIMA model (found out based on lowest AIC [Akaike information criterion] values), and the NNAR(neural network auto-regression) model was applied on the data series to check the efficacy of each model in the basis of the error statistic values among which NNAR has outperformed the other two models. Also, the medium-term forecasting of the next 25 days was conducted applying each model to check the robustness of the models.

The result would help the risk managers and the power market participants to decide which position to take while trading in the Indian electricity market especially while trading in the most complicated southern region, thereby leading to maximization of the profits.

Trading in the Indian electricity market is still at a very nascent stage, leading to a lot of scope in research and introduction of innovative products.

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About the Author

Ms. Sonal Gupta has more than eight years of teaching and industry experience. She is skilled in Energy derivatives and risk management, value chain, law and policy. She is a resilient education professional with a Master of Business Administration (MBA) focused in Energy Trading from University of Petroleum and Energy Studies, Dehradun. She has published several national and international papers in journals of repute and also has presented papers in International conferences.

Currently associated with the University of Petroleum and Energy studies as an Assistant Professor in the Department of Energy Management, School of Business, Ms. Sonal Gupta wants to pursue her career as a researcher in the area of risk assessment and modeling using more sophisticated tools.

List of Publications

- Gupta, S., Chakrabarti, D., Roy, H (2018). Indian Energy Exchange Day Ahead Market: The issue of stationarity. Journal of Emerging Technologies and Innovative Research. ISSN:2349-5162, Vol.5, Issue 8, page no. 632-638, August-2018, Available: http://www.jetir.org/papers/JETIR1808734.pdf
- Gupta, S., Chakrabarti, D., Roy, H (2018). Indian Energy Exchange Day Ahead Market: Effects of Volatility on profitability. Journal of Emerging Technologies and Innovative Research. ISSN:2349-5162, Vol. 5, Issue 9, page no. 306-311, September-2018, Available:http://www.jetir.org/papers /JETIR1809063.pdf
- Gupta, S., Chakrabarti, D., Roy, H (n.d.). Electricity prices determinants: India's perspective. International Journal of Business Excellence (DOI no.: 10.1504/IJBEX.2019.10019286)

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