

Electricity Price Forecasting of Green Day-Ahead Market in India Using Garch Model

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Abstract

Introduction to Electricity Market has facilitated Renewable energy trading as a hope to tackle climate change and improve India's energy economy. Within the energy exchange, Green Day Ahead market has been studied thoroughly as it is the world's first market that trades in only renewable energy. Hourly MCPs for 365 days have been considered and the approach used is the GARCH(1,1) Model. The hourly returns have been assumed to be a skewed-normal distribution; conditions have been fulfilled for the studied time series and the Model is conducted. The Garch Model has been found to be a robust model for this time series analysis. A risk mitigation solution for high volatility forecasting has also been provided.

Keywords: Indian Electricity Market, GDAM, Price volatility, GARCH Model

1. Introduction

India stands at the forefront of the global battle against climate change, propelled by its burgeoning renewable energy sector. It has witnessed remarkable growth in recent years, fuelled by supportive government policies, technological advancements, and increasing investment. Solar, wind, biomass, and hydroelectric power constitute India's primary sources of renewable energy.

The Energy generation market in India is quite fragmented. Big Power Companies can directly approach the State government to supply electricity and do not require an intermediary. However, many small companies that are generating small volumes of electricity need an exchange to help them find potential buyers on a short-term basis. This challenge along with long-term inflexible PPAs (Power purchase agreements) led to the establishment of India's first power exchange market, which stands as a landmark moment in the nation's energy sector evolution. Introduced on June 27, 2008, by the Indian Energy Exchange Limited (IEX), this innovative platform marked a pivotal shift towards a more transparent, efficient, and competitive electricity trading system. Power Exchanges enable buyers and sellers to complete transactions with as little as one hour's notice or even up to a year. As a result, if a DISCOM (distribution company) experiences a surge in demand, it can purchase the item on the exchange and receive delivery in just one hour.

The Green Day Ahead Market (GDAM), introduced on October 25, 2021, refers to a segment within the electricity market designed to facilitate the trading of green energy, specifically renewable

energy sources, on a day-ahead basis. India is the only large electricity market in the world to implement a Green Day Ahead Market (GDAM) exclusively for renewable energy. This type of market allows for the advance purchase and sale of electricity that will be generated from renewable sources such as wind, solar, hydro, and biomass for delivery the following day. This initiative is aimed at enhancing the adoption of renewable energy in India's energy mix and supporting the country's ambitious sustainability goals.

An REC is also awarded for each megawatt-hour (MWh) of electricity produced using qualified renewable energy sources. Renewable Energy Certificates (RECs) are a market-driven tool that India uses to encourage the production of renewable energy and make meeting renewable energy targets easier.

Now a market with more than 4000 open access customers, forecasting spot prices is extremely important. Forecasted electricity prices using different methods/models embed crucial signal and information for power market participants which play a major role in devising bidding strategies for maximizing future benefits/utilities. Spot electricity prices are more volatile than any other commodity and are known for extreme price volatility.

REVIEW OF LITERATURE

a) Renewable Energy and Risk

Numerous reports have found that the main reason RET is not deployed is because of higher investment risks (Steggals et al., 2017; Energiewende, 2018). As risk and return profiles change over the lifecycle of clean energy projects, different investors of both debt and equity are present at different stages wherever their risk appetites are matched (Bella Tonkonogy et al.).

Nearly 90% of the power produced in India is locked up in 25-year PPAs, which are inflexible and prevent DISCOMs from investigating more affordable power options on the market. Long-term PPAs do not provide flexibility because the buyer must pay a fixed cost per unit for the contractual amount of electricity, regardless of how much power they use at any given time. Among the PPAs there also exists a risk called the off-taker risk, which is a power purchase agreement (PPA) between the producer and the buyer (also known as off-taker) that is typically negotiated before the commencement of a project with the guarantee of purchase of a certain amount of electricity at a certain price point. This agreement can also be structured like a forward contract. Although it is similar to a forward contract, it differs in the risk that the off-takers might not fulfill their contractual agreement. (Arsalan Ali, Gireesh Shrimali, CPI, 2016). This is because, major off-takers, which are usually the DISCOMS (State level public sector electricity distribution companies) are running under losses of approximately INR 2.52 trillion, with a collective debt of INR 3.04 trillion leading them on the brink of collapse (Livermint, 2014). Among these 3.04 trillion, DISCOMs owe over INR 1.2 trillion in outstanding payments to Power generators for power purchased under PPAs (Surge Capital, 2022).

b) The Power Market

Author G.P Girish explains in his paper that Electricity is a very distinctive commodity which cannot be cost-effectively stored and the end-user demand exhibits strong seasonality at annual, monthly, weekly, daily and intra-day levels [4]. The electricity sector in India has been opened up for 100% Foreign Direct Investment (FDI) in power Generation, Distribution and power trading. In the last few decades, electricity markets worldwide are gradually transforming from being highly regulated by the Governments of the respective countries into deregulated and competitive markets and the Indian Electricity market is the latest entrant to this list. With the deregulation and increased competition, today, participants of power markets are facing new challenges. Events such as non-availability of resources (e.g., variation or shortage of coal for thermal power stations), power plant outages, flawed transmission grid reliability or breakdown of electrical transformers tend to have tremendous effects on electricity spot prices.

Electricity price forecast is therefore extremely important for all market players, and in particular for generating companies; they must set up bids for the spot market in the short term, they have to define contract policies in the medium term (how much energy must be sold by contract and at what price) and they must define their expansion plans in the long term. (Michele Binini, et al.)

DATA

In this study, we consider the Green Day-Ahead electricity price forecasting through the standard GARCH model. Day-ahead spot electricity market typically consists of 24 hourly auctions that take place simultaneously one day in advance. [5]

GDAM is a part of DAM, wherein the renewable energy contracts are traded on an FCFS (First come first serve) basis in the first round and when the volume for Green energy transactions is cleared, the bidding for non-renewable energy contracts in the Day-ahead market starts.

The study has used publicly available data given by the CERC, RLDC and IEX. Hourly logarithmic returns of Market clearing prices (MCP) of GDAM have been taken and forecasting performance is evaluated for a period from January 1, 2023 to December 31, 2023 accounting for 365 days and 8760 observations.

GARCH (1,1) MODEL

Forecast for GARCH models depend on the weighted sum of past squared residuals and past variance forecasts. The model typically consists of two components:

1. Autoregressive (AR) component: This component models the dependence of the current variance on past variances. It essentially captures the persistence of volatility. AR helps in understanding and forecasting the behavior of financial time series and is widely used in risk management and financial modeling.
2. Conditional heteroscedasticity (ARCH): This component captures the impact of past squared errors on the current variance.

Here, conditional variance is used which means that this is the kind of variance that changes its value based on pieces of data or given information. Conditional variance is different from unconditional variance, which is the typical σ^2 . It allows for the clustering of volatility (fig).

$$Var(\varepsilon_t) = \sigma_{t+1}^2 = \alpha_0 + \alpha_1 \sigma_t^2 \quad (1)$$

Here, σ_{t+1}^2 is the volatility tomorrow whereas, r_t^2 (or σ_t^2) is the volatility today. In addition, $Var(\epsilon_t)$ variance of error terms (error terms refer to the return residuals for a mean process) which also constitutes to volatility. An error term essentially means that the model is not completely accurate and results in differing results during real-world applications.

The GARCH (p,q) model for conditional variance follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^q \beta_i \sigma_{t-i}^2 \quad (2)$$

Where ω is the constant or unconditional variance;

ϵ_{t-i}^2 is the previous error term

σ_{t-i}^2 is the (t-i) day's forecast

Here, $\omega > 0, \alpha_1, \alpha_2 \dots \dots \dots \alpha_p \geq 0$, and, $\beta_1, \beta_2 \dots \dots \dots \beta_p \geq 0$, and $\sum_{i=1}^p \alpha_i + \sum_{j=1}^q \beta_j < 1$ is necessary and sufficient for stationarity.

In GARCH(p,q), p is the ARCH term and q is the GARCH term. The ARCH model is not quite efficient in dealing with persistent volatility. Since the GARCH model assumes the volatility of the previous day, it is going to make the resulting time series experience fewer bursts.

The normal GARCH model assumes:

$$R_t = \mu_t + \epsilon_t \quad (3)$$

where μ_t is the underlying mean and ϵ_t are the residuals (errors) which the mean cannot explain $\epsilon_t \sim N(0, \sigma_t^2)$ [which means ϵ_t is normally distributed]

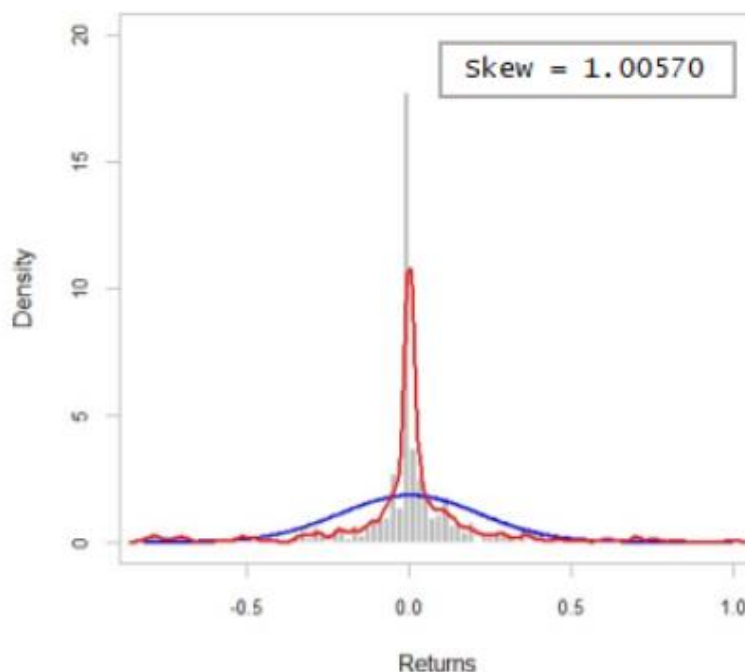


Figure 1. Distribution of daily GDAM log returns for 2023

It is not realistic to assume a normal distribution when analyzing electricity price returns using GARCH model. The normal distribution is not consistent because when returns experience volatility, the prices go to their extremes resulting in crashes and non-normality in the return chart. Compared to the normal, the study’s actual return distribution is much more narrow-peaked.

This distribution is fat-tailed implying that there exists many extreme standardized returns. Here, the distribution is positively skewed meaning that the positive extremes occur more than the negative ones.

Therefore, this study has used the GARCH model assuming a skewed normal distribution for the accuracy of results.

Empirical findings

1. Stationary data

Table 1. ADF Test for Stationarity

Test (Augmented Dickey-Fuller)	
Alternate hypothesis	Stationary
p-value	0.01
Note	In adf. test: p-value smaller than printed p-value
Lag order()	7

For checking the stationarity of the time series, Augmented Dickey-Fuller test is performed.

Under this hypothesis test,

H_0 = Series is non-stationary

H_A = Series is stationary

We observe in Table 1. that the p-value is less than 0.05 or less than 5% level of significance.

Hence, we reject the null hypothesis, and accept the alternate hypothesis which says that the time series is stationary, thus fulfilling the first condition.

2. Volatility clustering

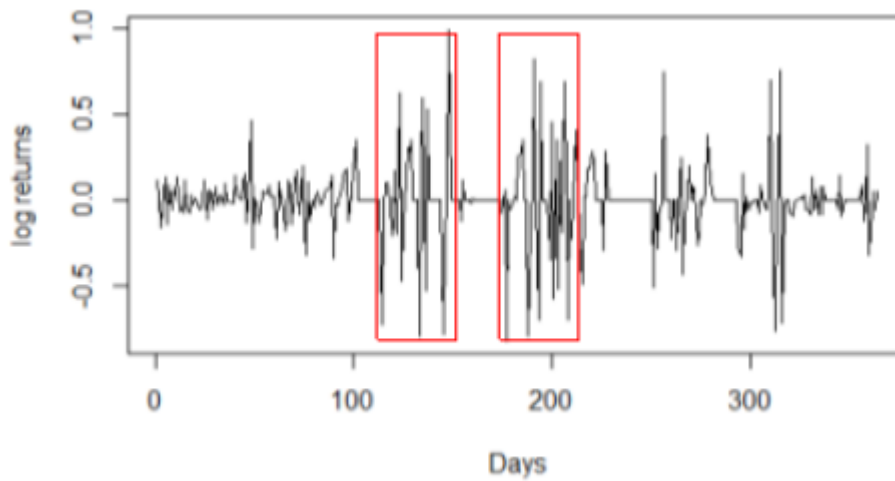


Figure 2. Volatility Clustering of log returns of GDAM

In finance, volatility clustering, first noted by Mandelbrot (1963), means that large changes tend to be followed by large changes, and small changes tend to be followed by small changes. The propensity of these large changes or smaller changes tends to cluster together resulting in longer periods of persistent varying volatility. Here in Fig 2. We can observe clustering at several places.

3. Arch effect

Table 2. ARCH LM Test for ARCH effect

Test (Arch LM-test)	
Null hypothesis	No ARCH effects
p-value	0.01
Chi-squared	37.405
df	12

The ARCH effect indicates that the volatility does not remain constant over time. It detects whether there is a presence of autocorrelation in the squared residuals of a time series, indicating that the volatility of the series is not constant over time. In the ARCH LM test, the

H_0 = There is no ARCH effect

H_A = There is an ARCH effect

We observe that the p-value in this test is 0.01 (< 0.05). Hence, we reject the null hypothesis and conclude that there is an ARCH effect and a higher order ARCH model is required to model the heteroscedasticity.

The above three were the conditions for creating the GARCH (1,1) model. And the time series being studied has passed all the conditions in order to carry out this model.

RESULTS

Table 3. GARCH (1,1) test result

Name of return	AR[1]	MA[1]	α_0 (Constant)	α (ARCH effect)	β (GARCH effect)	$\alpha + \beta$
GDAM	0.69 (0.00)*	-0.94 (0.00)*	0.00 (0.04)*	0.22 (0.01)*	0.70 (0.00)*	0.92

*P-values are included in the brackets and * denotes the significance level of 5% = rejection of null hypothesis*

Table 3. shows that all parameters are significant GARCH components at the 5% significance level. This suggests that periods of high volatility tend to cluster together over time. The combined effect of ARCH and GARCH components is near 1, indicating that the volatile nature is persistent and clustering for maximum series. Therefore, we conclude that our GARCH model is robust.

Table 4. Weighted Ljung-Box test on r^2

Name of return	Ljung-Box test on standardized residuals			Ljung-Box test on standardized squared residuals		
	Lag[1]	Lag	Lag	Lag[1]	Lag	Lag
		$[2*(p+q)+ (p+q)- 1][5]$	$[4*(p+q)+ (p+q)-1][9]$		$[2*(p+q)+ (p+q)-1][5]$	$[4*(p+q)+ (p+q)-1][9]$
GDAM	1.186 (0.27)	2.294 (0.87)	3.331 (0.83)	0.43 (0.51)	0.85 (0.89)	1.41 (0.96)

The weighted Ljung-Box test ((Ljung & Box, 1978) is used on standardized residuals and standardized squared residuals to check if the GARCH (1,1) model removes the serial dependence of the residuals. The test checks for autocorrelation at lag $k>0$ and the null hypothesis is that the residuals are independently and identically distributed. This test can also be explained by the autocorrelation functions of log returns of GDAM MCPs showing negligible correlation.

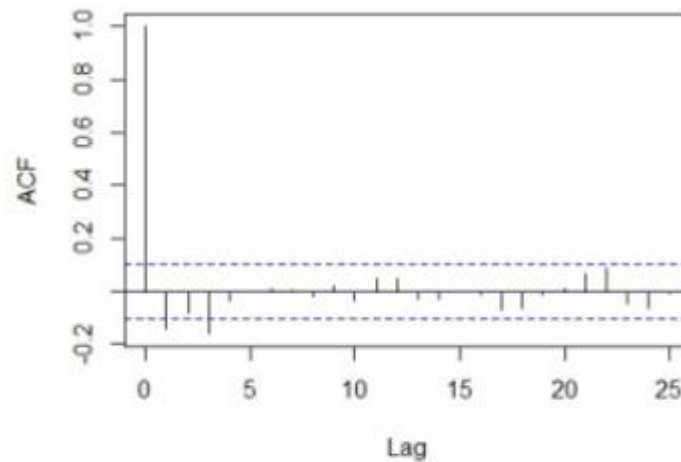


Figure 5. ACF of GDAM log returns

Figure 5. shows that the null hypothesis of no autocorrelation at lag $k > 0$ cannot be rejected at the 5% significance level, indicating that the GARCH (1,1) model is successful in removing serial dependence in both the standardized residuals and standardized squared residuals. The overall results suggest that the GARCH (1,1) model adequately captures the volatility dynamics of the return series.

Conclusion

Volatility through the GARCH model shows us a more accurate picture of price fluctuations in the Green Day Ahead Market. Electricity prices depend on electricity demand and requirements from individual buyers and distribution companies. Unlike stock returns, which depend on a variety of factors like Market Value, historical price data, and speculation, electricity spot prices hardly work like that. Therefore, mathematical prediction of volatility for electricity prices is quite difficult in real life making it a very risky investment.

However, we can still partly overcome this problem by introducing Forwards and Futures Contract will mitigate risks associated with energy trading. Generators will have the security of knowing someone will buy their electricity and the suppliers will have the security of knowing that they will have the supply on time to meet customer demand. By locking in the price well ahead of delivery, generators and suppliers will reduce their exposure to continually changing and volatile spot market prices. This would also reduce counterparty risk, as legal obligations will be involved.

As the market matures, continuous improvements in forecasting techniques, grid infrastructure, and regulatory support will be essential to fully realize the potential of the GDAM. The success of this market can serve as a model for other countries aiming to integrate renewable energy more effectively into their power systems.

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