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# Powering India's Future: The Road To 500 Gw Renewable Energy By 2030

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**Abstract**
As India continues to experience rapid economic growth and urbanization, the demand for electricity is rising steadily. To meet this demand sustainably, the country has set ambitious goals for expanding its renewable energy capacity, targeting 500 GW of non-fossil fuel-based capacity by 2030. This paper aims to forecast the installed electricity generation from renewable energy per capita in India until 2030, focusing on solar, wind, hydro, and biomass energy. Using historical data from 2014 to 2022.Additionally, the research considers key exogenous factors such as population growth, technological advancements, and policy shifts in India's renewable energy landscape. The results indicate a significant increase in per capita renewable energy generation, primarily driven by solar and wind power. However, challenges related to grid integration, energy storage, and regional disparities in energy access may affect the realization of these projections. This study provides valuable insights for policymakers, energy planners, and stakeholders in India's renewable energy sector, highlighting the need for continued investments in infrastructure and technology to ensure equitable and sustainable energy access across the country.

**Key words:** Renewable Energy, Solar Energy, Wind Energy, Energy Forecasting, Regression Analysis, Energy Transition, Energy Demand Forecasting, Green Energy, Energy Policy, 500 GW Renewable Energy Target, Sustainable Development, Energy Systems Modeling, Energy Supply and Demand, India's Renewable Energy, Energy Planning, Climate Change Mitigation, Carbon Emission Reduction, Clean Energy Future, Energy Infrastructure, Forecasting Models, Statistical Modeling, Linear Regression, Time Series Forecasting, Data-driven Decision Making, Energy Economics, Energy Scenario Analysis, Renewable Energy Integration, Green Growth Strategy, Electricity Generation Forecasting, Energy Transition in India

## 1. Introduction

- **Background:**
  - India's energy sector is at a crossroads. The country is experiencing rapid economic growth, but its electricity demand is rising at an unsustainable rate, leading to significant pressure on the grid and fossil fuel-based generation.
  - India has recognized the importance of renewable energy in this context and has set ambitious targets for renewable energy installation, especially solar and wind.
  - By 2030, India aims to achieve 500 GW of non-fossil fuel capacity, with renewables playing a major role.
  - Forecasting the installed renewable energy capacity per capita can provide insights into the pace of this transition.
- **Problem Statement:**
  - The renewable energy transition in India is crucial for both energy security and environmental sustainability. However, reliable forecasts of renewable energy generation per capita are lacking, which hinders effective policy planning and resource allocation.

- **Research Objectives:**
  - To forecast the installed capacity of renewable energy generation per capita in India until 2030.
  - To assess the impact of renewable energy expansion on electricity generation and energy access at a per capita level.
  - To evaluate how policy, technological advancements, and economic factors will influence renewable energy growth.
- **Research Questions:**
  - What are the growth trends in renewable energy generation in India?
  - How can the per capita renewable energy generation be projected accurately?
  - What are the main factors that influence the forecast for renewable energy in India?

## 2. Literature Review

- **Renewable Energy Landscape in India:**
  - India is one of the world's largest renewable energy producers, with significant investments in solar, wind, hydro, and biomass energy.
  - The government has taken strides to encourage clean energy through policies like the National Solar Mission, the National Wind Energy Mission, and various state-level initiatives.
  - India's renewable energy growth has been impressive, but challenges like grid integration, financing, and land acquisition persist.
- **Studies on Renewable Energy Forecasting:**
  - Previous studies in other countries show that renewable energy capacity can be forecasted based on both historical data and external factors like technological changes and policy shifts.
  - A key challenge in forecasting for India is the high variability in renewable energy sources like wind and solar, which require sophisticated models to predict future capacity accurately.

## 3. Data Collection and Methodology

**Data Sources:**

- **Renewable Energy Capacity (Installed Capacity - MW):** Data from the Ministry of New and Renewable Energy (MNRE), International Renewable Energy Agency (IRENA), and the International Energy Agency (IEA).
- **Per Capita Electricity Consumption:** Statistics from the Central Electricity Authority (CEA), IEA, and the World Bank.
- **Population Data:** Historical and projected population data from the Census of India and United Nations Population Division.
- I have collected our secondary data from the following website:
  https://www.mospi.gov.in/

**Methodology:**

**<u>Regression Analysis</u>:**

- ❖ Decide on purpose of model and appropriate dependent variable to meet that purpose Decide on independent variables.
- ❖ Estimate parameters of regression equation.
- ❖ Interpret estimate parameters, goodness of fit and qualitative and qualitative assessment of parameters.
- ❖ Assess appropriateness of assumption.
- ❖ If some assumptions are not satisfied, modify and revise estimated equation.
- ❖ Validate estimated regression equation.

We will examine these steps with the assumption that purpose of model is already been decided and we need to perform remaining steps.

Here are some suggestions for variable to be included in regression analysis as independent variable.

**<u>AUTOCORRELATION</u>**

**<u>Detection methods:</u>**

➔ **Durbin Watson d Test:**

The most celebrated test for detecting serial correlation is that developed by statisticians Durbin and Watson. It is popularly known as the Durbin– Watson d statistic, which is defined as

$$d = \frac{\sum_{t=2}^{n}(\hat{u}_t - \hat{u}_{t-1})^2}{\sum_{t=1}^{n}\hat{u}_t^2}$$

This is simply the ratio of the sum of squared differences in successive residuals to the RSS. Note that in the numerator of the d statistic the number of observations is n− 1 because one observation is lost in taking successive differences. A great advantage of the d statistic is that it is based on the estimated residuals, which are routinely computed in regression analysis. Because of this advantage, it is now a common practice to report the Durbin– Watson d along with summary measures, such as $R^2$ , adjusted $R^2$, t, and F. Although it is now routinely used, it is important to note the assumptions underlying the d statistic.

1. The regression model should include the intercept term. If it is not present, as in the case of the regression through the origin, it is essential to rerun the regression including the intercept term to obtain the RSS.
2. The explanatory variables, the X's, are non-stochastic, or fixed in repeated sampling.
3. The disturbances $u_t$ are generated by the first-order autoregressive scheme: $u_t = \rho\, u_{t-1} + \varepsilon_t$. Therefore, it cannot be used to detect higherorder autoregressive schemes.
4. The error term $u_t$ is assumed to be normally distributed.
5. The regression model should not include the lagged value(s) of the dependent variable as one of the explanatory variables. Thus, the test is inapplicable for models of the following type:
$Y_t = \beta_1 + \beta_2X_{2t} + \beta_3X_{3t} + \cdots + \beta_kX_{kt} + \gamma Y_{t-1} + u_t$ , where $Y_{t-1}$ is the one period lagged value of Y. Such models are known as autoregressive models.
6. There are no missing observations in the data. Thus, in our regression for the period 1959–1998, if observations for, say, 1978 and 1982 were missing for some reason, the d statistic makes no allowance for such missing observations.

The exact sampling or probability distribution of the d statistic is difficult to derive because, as Durbin and Watson have shown, it depends in a complicated way on the X values present in a given sample. This difficulty should be understandable because d is computed from $u_t$ , which are, of course, dependent on the given X's. Therefore, unlike the t, F, or $\chi^2$ tests, there is no unique critical value that will lead to the rejection or the acceptance of the null hypothesis that there is no first-order serial correlation in the disturbances $u_t$. However, Durbin and Watson were successful in deriving a lower bound dL and an upper bound $d_U$ such that if the computed d is outside these critical values, a decision can be made regarding the presence of positive or negative serial correlation. Moreover, these limits depend only on the number of observations n and the number of explanatory variables and do not depend on the values taken by these explanatory variables. These limits, for n going from 6 to 200 and up to 20 explanatory variables, have been tabulated by Durbin and Watson and are reproduced in Appendix D, Table D.5 of D. Gujarati's book. µ

The actual test procedure can be explained better with the aid of Figure 5, which shows that the limits of d are 0 and 4. These can be established as follows. Expand the formula of d to obtain

$$d = \frac{\sum_{t=2}^{n}\hat{u}_t^2 + \sum_{t=2}^{n}\hat{u}_{t-1}^2 - 2\sum_{t=2}^{n}\hat{u}_t\hat{u}_{t-1}}{\sum_{t=1}^{n}\hat{u}_t^2}$$

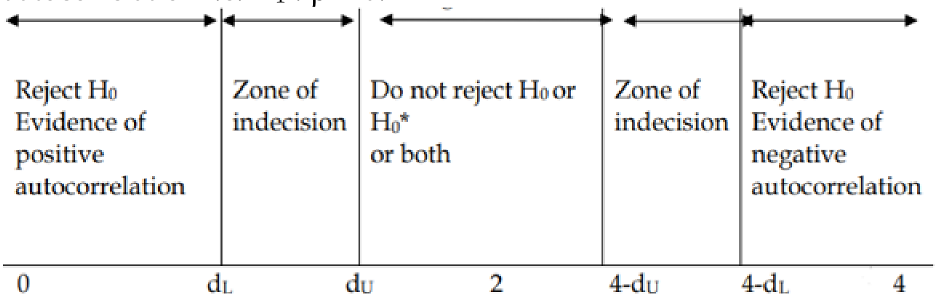
Since $\sum_{t=2}^{n}\hat{u}_t^2$ and $\sum_{t=2}^{n}\hat{u}_{t-1}^2$ differ in only one observation, they are approximately equal. Therefore, setting $\sum_{t=2}^{n}\hat{u}_t^2 \approx \sum_{t=2}^{n}\hat{u}_{t-1}^2$, we get,

$$d \approx 2\left(1 - \frac{\sum_{t=2}^{n}\hat{u}_t\hat{u}_{t-1}}{\sum_{t=1}^{n}\hat{u}_t^2}\right)$$

The mechanics of the Durbin–Watson test are as follows, assuming that the assumptions underlying the test are fulfilled:

1. Run the OLS regression and obtain the residuals.
2. Compute d.

3. For the given sample size and given number of explanatory variables, find out the critical $d_L$ and $d_U$ values.
4. Now follow the decision rules given in Table 5 for ease of reference, these decision rules are also depicted in the following Figure 5. Here we test $H_0$: No positive autocorrelation i.e. $H_0$: $\rho = 0$ against $H^*_0$: No negative autocorrelation i.e. $H_1 : \rho \neq 0$.




**Autocorrelation function plot (ACF):**

Autocorrelation refers to how correlated a time series is with its past values whereas the ACF is the plot used to see the correlation between the points, up to and including the lag unit. In ACF, the correlation coefficient is in the x-axis whereas the number of lags is shown in the y-axis.

- The Autocorrelation function plot will let you know how the given time series is correlated with itself

**Partial Autocorrelation Function plots (PACF):**

A partial autocorrelation is a summary of the relationship between an observations in a time series with observations at prior time steps with the relationships of intervening observations removed.
The partial autocorrelation at lag k is the correlation that results after removing the effect of any correlations due to the terms at shorter lags.

**Compound Model is best fitted so our equation model become as:**

$$E(Y_X) = \beta_0 \beta_1^x$$

Where, Y= Installed electricity generation capacity in renewable energy (in Watt)
X= Year $\beta_1$ = Coefficient of year **$\beta_0$=** Constant

**4. Analysis and Results**

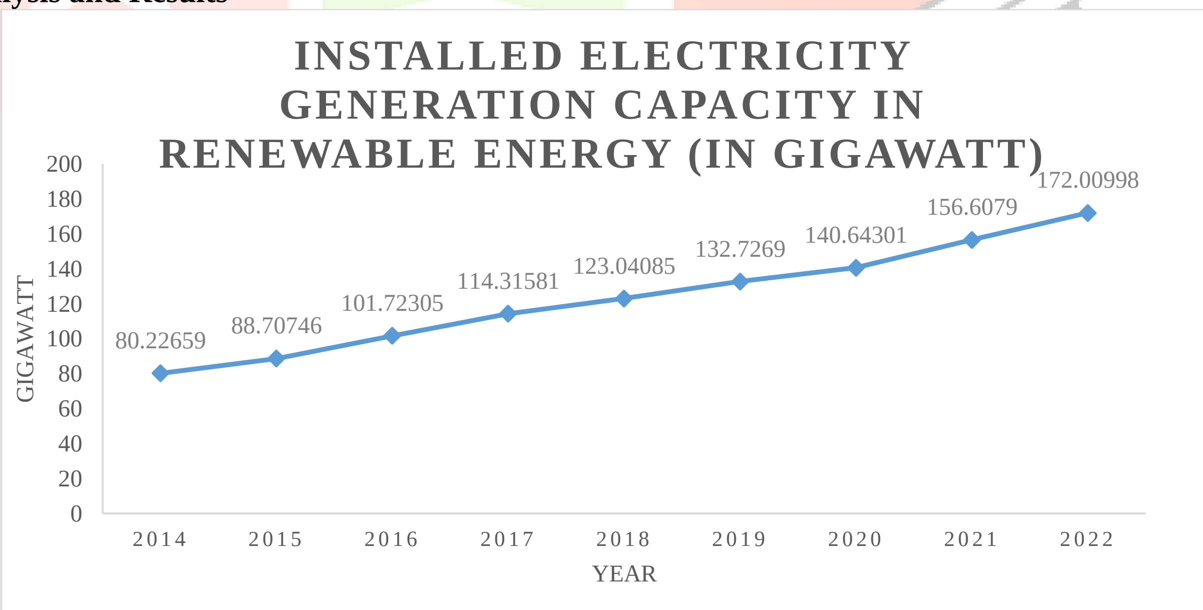



**Figure 1**: Trends in Global Renewable Energy Capacity Installation (in GW)

**Interpretation:-**

Here from the above graph we easily get idea of increase in Renewable Energy in successive year.

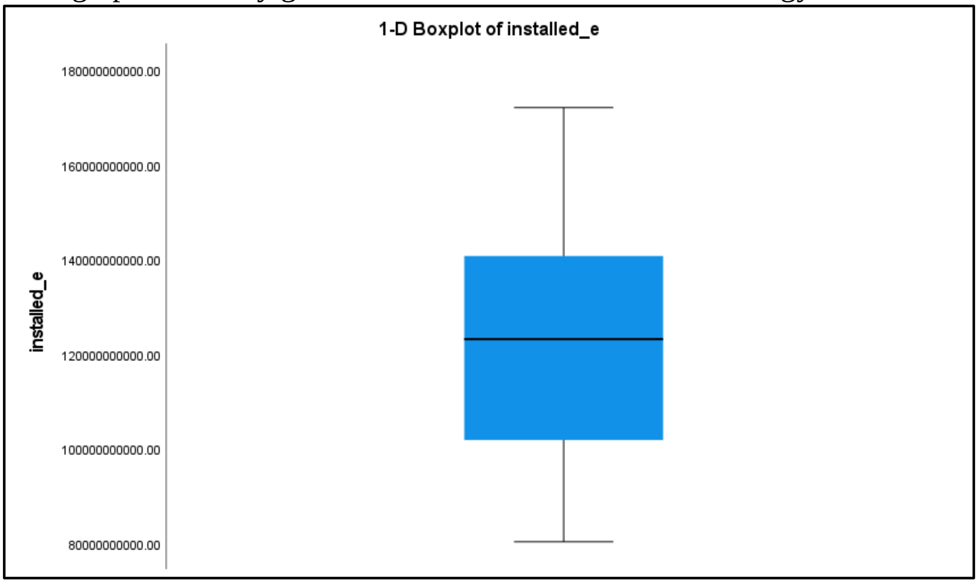



**Figure 2**: Boxplot Chart

**Interpretation:**

From the graph, there are no outliers in the given data.

**Detecting Problem of Autocorrelation:**

**(i) ACF and PACF Graph**

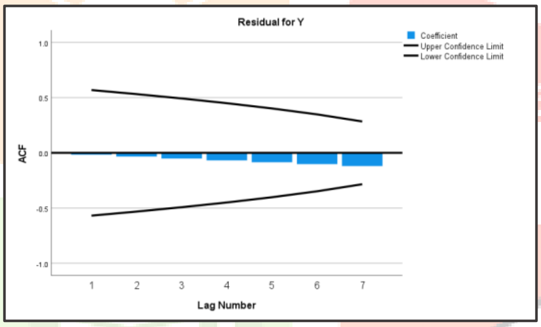



**Figure 3.1**: ACF Graph

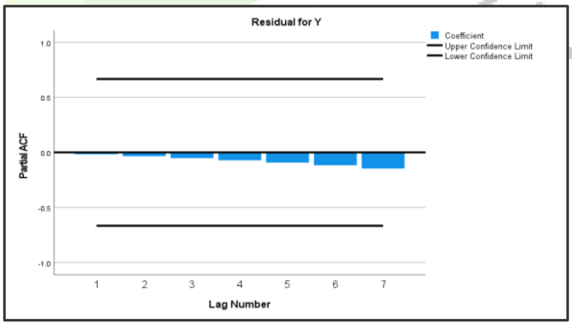



**Figure 3.2**: PACF Graph

**(ii) Durbin Watson Test**

**Model Summary**[b]

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Durbin-Watson |
|---|---|---|---|---|---|
| 1 | .996[a] | .993 | .992 | 2759356859 | 1.362 |

a. Predictors: (Constant), Year

b. Dependent Variable: Installed electricity generation capacity in renewable energy (in Watt)

**Table 1**: Durbin Watson Test

**Interpretation:**

DL = 0.554 & DU= 0.998 at 1% level of Significance so from the Durbin Watson test there is no autocorrelation problem.

**Compound Model Equation:-**

**Model Summary**

| R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|
| .995 | .989 | .988 | .028 |

The independent variable is Year.

**Table 2.1**: Model Summary

**ANOVA**

| | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Regression | .514 | 1 | .514 | 642.416 | <.001 |
| Residual | .006 | 7 | .001 | | |
| Total | .520 | 8 | | | |

The independent variable is Year.

**Table 2.2**: ANOVA Table

**Coefficients**

| | Unstandardized Coefficients | | Standardized Coefficients | | |
|---|---|---|---|---|---|
| | B | Std. Error | Beta | t | Sig. |
| Year | 1.097 | .004 | 2.704 | 273.849 | <.001 |
| (Constant) | 9.195E-71 | .000 | | . | . |

The dependent variable is ln(Installed electricity generation capacity in renewable energy (in Watt)).

**Table 2.3**: Coefficients Table

**Conclusion:**

Here 98% $R^2$ which mean that explanatory variable more explain the dependent variable and we observe that In the Compound model is the best fit among all the models as the standard error of the estimate is less and the coefficients are also significant with less standard error.

**Forecasting:**

**Forecasted Installed electricity generation capacity in renewable energy (in Gigawatt) up-to 2030.**

| Year | Installed electricity generation capacity in renewable energy (in Gigawatt) |
|---|---|
| 2023 | 190.454000000 |
| 2024 | 208.923000000 |
| 2025 | 229.183000000 |
| 2026 | 251.407000000 |
| 2027 | 275.787000000 |
| 2028 | 302.531000000 |
| 2029 | 331.868000000 |
| 2030 | 364.050000000 |

**Table 3.1**: Forecasted Installed Capacity of Renewable Energy (in GW)

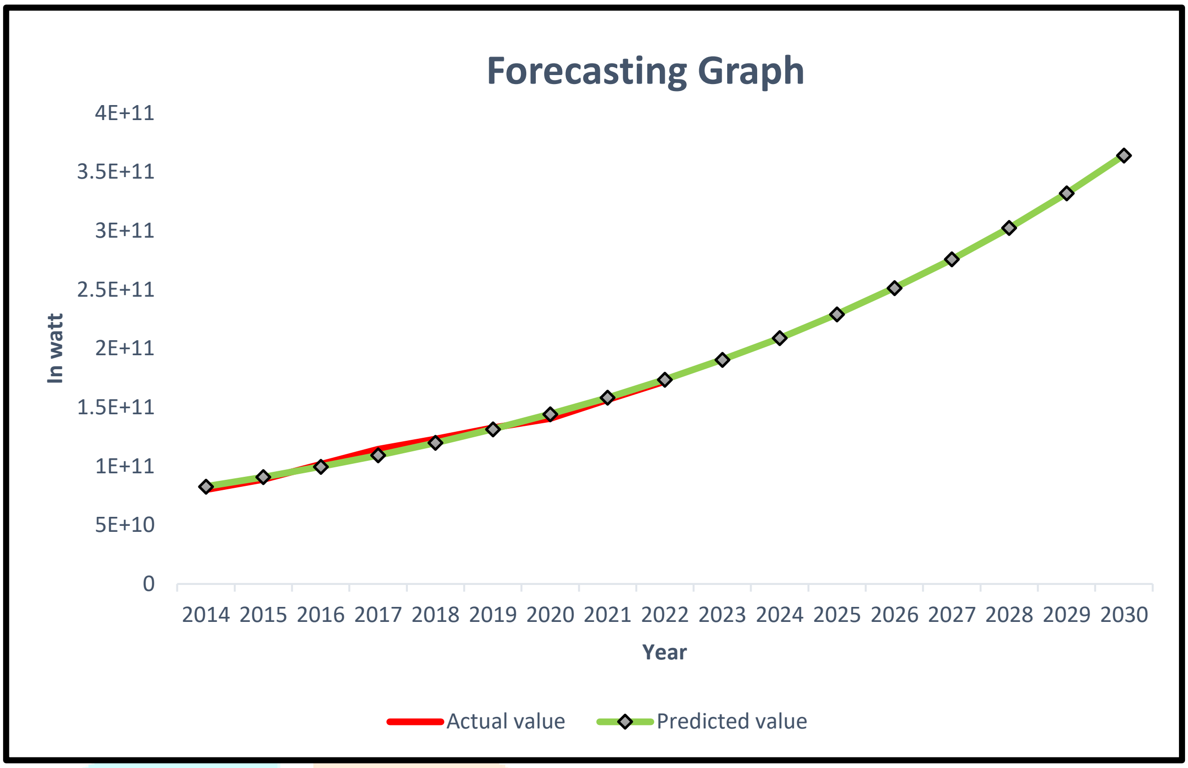



**Figure 4.1**: Renewable Energy Capacity Forecast: Growth Projections (in GW)

**Forecasting:**

**Forecasting the installed renewable energy capacity per capita (in Watt) up-to 2030.**

| Year | Watts per capita |
|---|---|
| 2023 | 135.9663505 |
| 2024 | 147.8237941 |
| 2025 | 160.7275928 |
| 2026 | 175.0164353 |
| 2027 | 190.5854941 |
| 2028 | 207.5500513 |
| 2029 | 226.0382673 |
| 2030 | 246.183636 |

**Table 3.2**: Forecasted Installed renewable energy capacity per capita (in Watt)

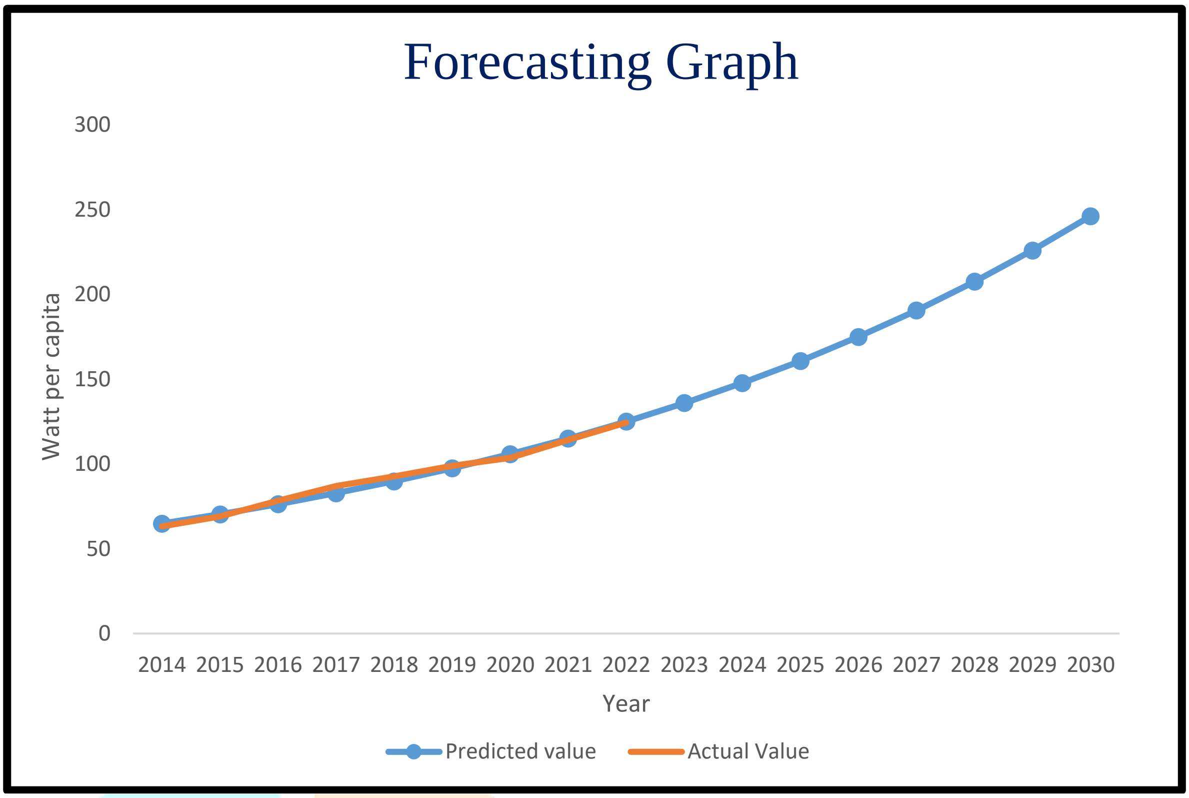



**Figure 4.2**: Forecasted Watts per Capita in Renewable Energy Generation (in watt)

## 5. Conclusion:

The forecasting analysis suggests a substantial increase in India's installed renewable energy generation capacity by 2030. The exponential model demonstrated the best predictive performance, with an $R^2$ value of 98%. These findings highlight the rapid growth of renewable energy and the need for continued investments in infrastructure to sustain this upward trend. The increasing per capita energy availability indicates that India is progressing towards achieving its sustainable energy goals. Future research should focus on incorporating additional factors such as policy changes, technological advancements, and economic conditions to refine these projections further.

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